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THESIS

STATISTICAL ANALYSIS OF THE NAVAL INVENTORY CONTROL POINT REPAIR TURN-AROUND TIME FORECAST MODEL

by

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June 2000

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ABSTRACT ***(maximum 200 words)***

Accurate forecasting of repair turn-around time (RTAT) of United States Navy depot level repairable items is critical to achieving optimal service levels while minimizing procurement and repair costs. The Navy's Inventory Control Point has developed a forecast model that uses sophisticated Statistical Process Control techniques and non-parametric algorithms to forecast RTAT. This thesis attempts to validate the Navy's RTAT forecast model by comparing its performance to those of simple time series forecasting methods. It was found that the assumptions implicit in the UICP RTAT forecast model have a significant impact on forecast accuracy. In addition to documenting these model properties, a goal of this thesis is to identify variables that the UICP model does not use in RTAT forecasting which may improve its accuracy. The research focuses on data for repairable items that have high dollar value and the greatest number of repair transactions per quarter.

Results show that the Navy's model is not consistently more accurate than any of the alternative techniques examined, and that it tends to ignore many large RTAT observations, causing it to under-forecast RTAT. Thesis research also reveals that accounting for differences in disparate designated overhaul points may significantly improve the prediction of RTAT. Finally it is shown that additional variables, derived from a NAVICP Philadelphia database and designed to capture the queueing aspect of the repair process, may significantly improve the prediction of RTAT. These findings point to the use of queueing information to obtain more accurate RTAT forecasts.

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STATISTICAL ANALYSIS OF THE NAVAL INVENTORY CONTROL POINT REPAIR TURN-AROUND TIME FORECAST MODEL

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Accurate forecasting of repair turn-around time (RTAT) of United States Navy depot level repairable items is critical to achieving optimal service levels while minimizing procurement and repair costs. The Navy's Inventory Control Point has developed a forecast model that uses sophisticated Statistical Process Control techniques and non-parametric algorithms to forecast RTAT. This thesis attempts to validate the Navy's RTAT forecast model by comparing its performance to those of simple time series forecasting methods. It was found that the assumptions implicit in the UICP RTAT forecast model have a significant impact on forecast accuracy. In addition to documenting these model properties, a goal of this thesis is to identify variables that the UICP model does not use in RTAT forecasting which may improve its accuracy. The research focuses on data for repairable items that have high dollar value and the greatest number of repair transactions per quarter.

Results show that the Navy's model is not consistently more accurate than any of the alternative techniques examined, and that it tends to ignore many large RTAT observations, causing it to under-forecast RTAT. Thesis research also reveals that accounting for differences in disparate designated overhaul points may significantly improve the prediction of RTAT. Finally it is shown that additional variables, derived from a NAVICP Philadelphia database and designed to capture the queueing aspect of the repair process, may significantly improve the prediction of RTAT. These findings point to the use of queueing information to obtain more accurate RTAT forecasts.

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TABLE OF CONTENTS

LIST OF FIGURES

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LIST OF ACRONYMS

DOP	Designated Overhaul Point
FTM	Forecast Tracking Mean
MAPD	Mean Absolute Percentage Deviation
MPE	Mean Percentage Error
NIIN	National Item Identification Number
NAVICP	Naval Inventory Control Point
NAVICP-Mech	Naval Inventory Control Point, Mechanicsburg, PA
NAVICP-Phil	Naval Inventory Control Point, Philadelphia
RTAT	Repair Turn-Around Time
SPC	Statistical Process Control
TAT	Turn-Around Time
UICP	Uniform Inventory Control Program

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LIST OF TERMS

Bias	A measure of the propensity of a forecast methodology to consistently under- or over-forecast
Candidate RTAT forecast	Forecast produced by one of the UICP RTAT forecast model forecasting methodologies, but which has not yet passed through automatic update tests.
Completion RTAT	The repair time of an item completed in a particular quarter.
Deviation	Measure of forecast accuracy
Exception item	A repairable item for which any forecast produced by the UICP RTAT forecast methodology must be validated by an item manager.
Exclusion item	An item managed by NAVICP for which a forecast will not be computed by the UICP RTAT forecast model.
Fence	The date used to demarcate the latest change in the distribution of RTAT as the repair process evolves across time.
File RTAT	RTAT forecast on file. Computed in the previous quarter.
Induction RTAT	The repair time of an item sent out for repair in a particular quarter relative to that quarter.
Item manager	The person responsible for the overall inventory management of a particular item.
Process change	An abrupt change in the distribution of repair times.
Repair completion date	The date of repair completion. The date that the designated overhaul point transfers custody of the overhauled item to a stock point.
Repair time	RTAT. The amount of time an item spends in repair. Includes actual repair time plus time waiting for repair.
Repair price	The price paid to repair an item.
Standard Price	The price paid for a new or overhauled item.

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EXECUTIVE SUMMARY

To efficiently manage its stocks of repairable items, the Naval Inventory Control Point (NAVICP) must be able to forecast repair times of the items that it sends to overhaul points for repair. Because repair turn-around time (RTAT) for several thousand items must be forecast on a quarterly basis, NAVICP developed an automated forecasting tool, known as the Uniform Inventory Control Program (UICP) RTAT forecast model, that uses a common methodology for each item. The research described in this thesis considers the accuracy of the model from several different perspectives:

1) The prediction accuracy of the UICP RTAT forecast model across a subset of repairable items that were chosen to represent high-value, high-volume repair activities;

2) The accuracy of alternative forecasting methodologies, including exponential smoothing, four-quarter moving averaging, and use of the previous quarter average RTAT value;

3) The validity of assumptions implicit in the UICP RTAT forecast model and the impact that these assumptions have on forecast accuracy;

4) The ability of additional predictor variables from the same data used in current RTAT forecasting to improve the prediction of repair times.

None of the simple alternative methodologies that are considered in this thesis are found to perform better than the UICP RTAT forecast model. Conversely, forecasts produced by the UICP model are not consistently more accurate than forecasts produced by any of the alternative methodologies.

The UICP RTAT model forecasts are found to consistently underforecast RTAT. One source of underforecasting is the outlier screening used in the UICP model, which tends to exclude many more large RTAT values than small ones. It is found that a simple, but effective remedy for the problem of excluding disproportionate numbers of

large RTAT observations is to apply a logarithm transformation of the RTAT values before the UICP RTAT model begins its forecasting. The transformation substantially reduces the impact of outliers, but did not solve the under-forecasting problem. The benefit of using the logarithmic transformation is that it may reduce or eliminate the need for outlier exclusion. Consequently the amount of information discarded may be reduced.

For items that are sent to more than one designated overhaul point (DOP) for repair, it is found that accounting for the DOP may significantly improve the prediction of repair turn-around times. Some DOPs are found to take longer to repair a given item than others.

Because the UICP model forecasts RTAT based solely on repair transactions that have been completed, it ignores the present state of the repair process and the queueing aspect of this process. In conducting the thesis research, additional variables are derived from a NAVICP database to capture these aspects. It is found that significant improvement in the prediction of RTAT may be realized by considering the additional variables in a forecasting model. However, no clear or simple means are found by which the existing model could be modified in order to realize these gains. Adopting a regression approach in the forecasting model may be more difficult than incorporating the DOP factor, but in both cases results point to the use of queueing information to obtain more accurate RTAT forecasts.

This thesis makes two recommendations to improve the forecast accuracy of Navy repair turn-around times. They are as follows:

1. Incorporate DOP as a predictor of RTAT for items repaired by more than one DOP in future model development.

2. Identify and collect data on variables that capture the queueing aspect of the repair process. Incorporate the queueing aspect of the repair process in future forecast model development.

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I. INTRODUCTION

A. BACKGROUND

The United States Navy classifies its stocks of spare and repair parts as either consumable or repairable. Two Naval Inventory Control Point (NAVICP) sites manage Navy repairable items. Naval Inventory Control Point, Philadelphia (NAVICP-Phil) manages repairable items that support aviation assets, while Naval Inventory Control Point, Mechanicsburg (NAVICP-Mech) manages all other repairable items. Unlike consumables (or non-repairable parts), which are discarded at the time of failure, repairable items are forwarded to designated overhaul points. Those items identified as economically feasible to repair are restored to serviceable condition and those items that are not are condemned and processed for disposal. When an overhaul point repairs an item and classifies it as ready for issue, it is sent to a stock point to be issued to the next requisitioning customer. Repairable items are overhauled and returned to serviceable or "ready for issue" condition at costs that are significantly less than replacement costs and usually in less time than procurement lead times (Maher, 1993).

To efficiently manage their stocks of repairable items, NAVICP personnel must determine how many items to purchase, when to purchase them, how many items to repair, and when to repair them. To optimally calculate these quantities, accurate forecasting of several variables must be accomplished. Repair turn-around time (RTAT) is one of these variables. RTAT is defined as the actual amount of repair time that an item spends in the repair system. RTAT includes waiting time plus actual time needed to repair an item. Waiting time may include queuing time and time waiting for parts to arrive.

To develop an individual forecasting methodology for each of thousands of NAVICP managed repairable items would be an extremely large task. Instead, the NAVICP sites have jointly developed a program to automatically forecast RTAT for all repairable items. The program incorporates several types of time-series forecast methodologies that included both quantity-weighted averaging and exponential smoothing of historical RTAT data. However, because repair times for some items increase or decrease over time or may require special handling for various other reasons, the program has evolved into a complex algorithm that addresses contingencies such as trends, outliers, changes in the repair process, and situations where historical repair transaction data are limited.

B. MANUAL INTERVENTION IN FORECASTING RTAT

The Uniform Inventory Control Program (UICP) RTAT forecast model was developed to provide automated forecasts of RTAT for several thousand repairable items. However, it does not completely eliminate the need for human analysis. Changing the value of RTAT in the equations that NAVICP uses to manage its inventories affects repair schedules, procurement points, and inventory quantities. Erroneously high forecasts may result in unnecessary increases in inventories and thereby raise inventory costs, while erroneously low forecasts may result in inventories that are inadequate to support fleet requirements.

The UICP RTAT model therefore prompts for item manager inspection of RTAT forecasts under certain conditions. Item manager review is triggered when an RTAT forecast is considerably higher or lower than the previous quarter's forecast. Item manager review is also triggered by a value known as the "delta in turn-around time

demand value of repair requirement", which is a function of the RTAT forecast, average RTAT from the previous quarter, the repairable item dollar value, and quarterly demand. This value is compared against tabled parameters based on average RTAT from the previous quarter and the forecast method used by the model. Finally, item managers must automatically review the RTAT forecasts of certain items every quarter for various other reasons, including items of high mission criticality referred to as "exceptions". The forecasting does not automatically update the RTAT forecast of any item on the exception list; instead, updating must be performed manually.

When a repairable item is identified for review, item managers are required to check the validity of the model-generated forecast. The forecast that the model produced, the specific methodology that produced it, and all repair observation data are utilized in the review. Item managers may decide to use the forecast produced by the program or may assign their own. They may use their knowledge of specific repair processes, repair schedules, overhaul points, and any other information at their disposal. Personal-computer based software known as the Item Manager Toolkit is used to examine available repair data at both NAVICP sites.

This "Man in the Loop" aspect is an integral and perhaps necessary component of RTAT forecasting at NAVICP. Nonetheless, it is recognized that reducing human intervention while providing accurate forecasts would be a valuable feature of any modification to the RTAT forecasting tool. With the UICP RTAT forecast model, the level of item manager review may be controlled through modification of certain program parameters. However, neither a complete list of initial parameter values nor specific

goals for the number of items identified for review had been determined at the time this thesis was written.

In this thesis we consider the statistical validity of the model components that comprise the UICP RTAT forecast model. Possible system improvements achieved through item manager review and intervention are not considered in evaluating model performance.

The balance of the thesis is organized as follows. Chapter II gives a detailed description of the portion of the UICP RTAT forecast model that is studied in this thesis. Chapter III describes data used by the UICP RTAT forecast model that are also the basis of the thesis research. Analyses undertaken for individual repairable items, based on data that are described in Chapter III, are described in Chapter IV. Chapter V presents conclusions and makes recommendations of how the thesis research may improve the forecasting of repair time.

C. OBJECTIVES OF THE THESIS

The forecasts produced by the UICP RTAT forecast model are based entirely on the statistical properties of repair turn-around times of completed repair transactions. Although the model is intricate, it does not incorporate the queuing aspect of the repair system or any information about the repair process other than the date that an item was returned from repair, and the time required to perform the repair. In this thesis we examine additional sources of information that may improve the prediction of RTAT. One use of this information would be to develop a forecasting methodology that uses a larger set of variables for prediction. These variables may include the designated overhaul point that is assigned to make the repair, or the quantity of items still in repair at

the beginning of a quarter. Although this approach would increase the complexity of the RTAT forecasting model, more accurate forecasting of RTAT would improve the management of Navy inventories and may reduce the considerable amount of human intervention needed to apply the incumbent forecasting tool.

The objectives of this thesis are as follows:

1) Evaluate the UICP RTAT forecast model for its ability to predict RTAT across a range of repairable items.

2) Compare the UICP RTAT forecast model to standard time series forecasting methodologies, including previous quarter observed RTAT, four-quarter moving average, and exponential smoothing. Accuracy will be determined by measuring deviation and bias of the forecasts produced by the various methods.

3) Identify the assumptions implicit in the UICP RTAT forecast model and the impact that these assumptions have on forecast accuracy.

4) Identify additional predictor variables from the same data used in current RTAT forecasting, and evaluate their usefulness in predicting RTAT.

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II. THE UICP RTAT FORECAST MODEL

A. BACKGROUND

The UICP RTAT forecast model forecasts repair turn-around time (RTAT) for a repairable item using one of several methodologies. The forecast methodology is chosen depending on the total number of repair observations available, the number of quarters for which repair observations are available, quarterly demand, and a determination of process change or trend. Because this thesis restricts attention to repairable items with high volumes of available repair data, the forecasting methodologies designed for items with fewer than four repair observations are not examined. A description of the UICP RTAT forecast model is provided in this section. This description is summarized from the RTAT Narrative (FMSO, 1999), and from personal conversations with NAVICP personnel. The portion of the model considered in this thesis is coded as a set of S-Plus functions that are produced in Appendix A. A flowchart that illustrates the portion of the UICP RTAT forecast model described in this chapter is shown in Figure 2.1.

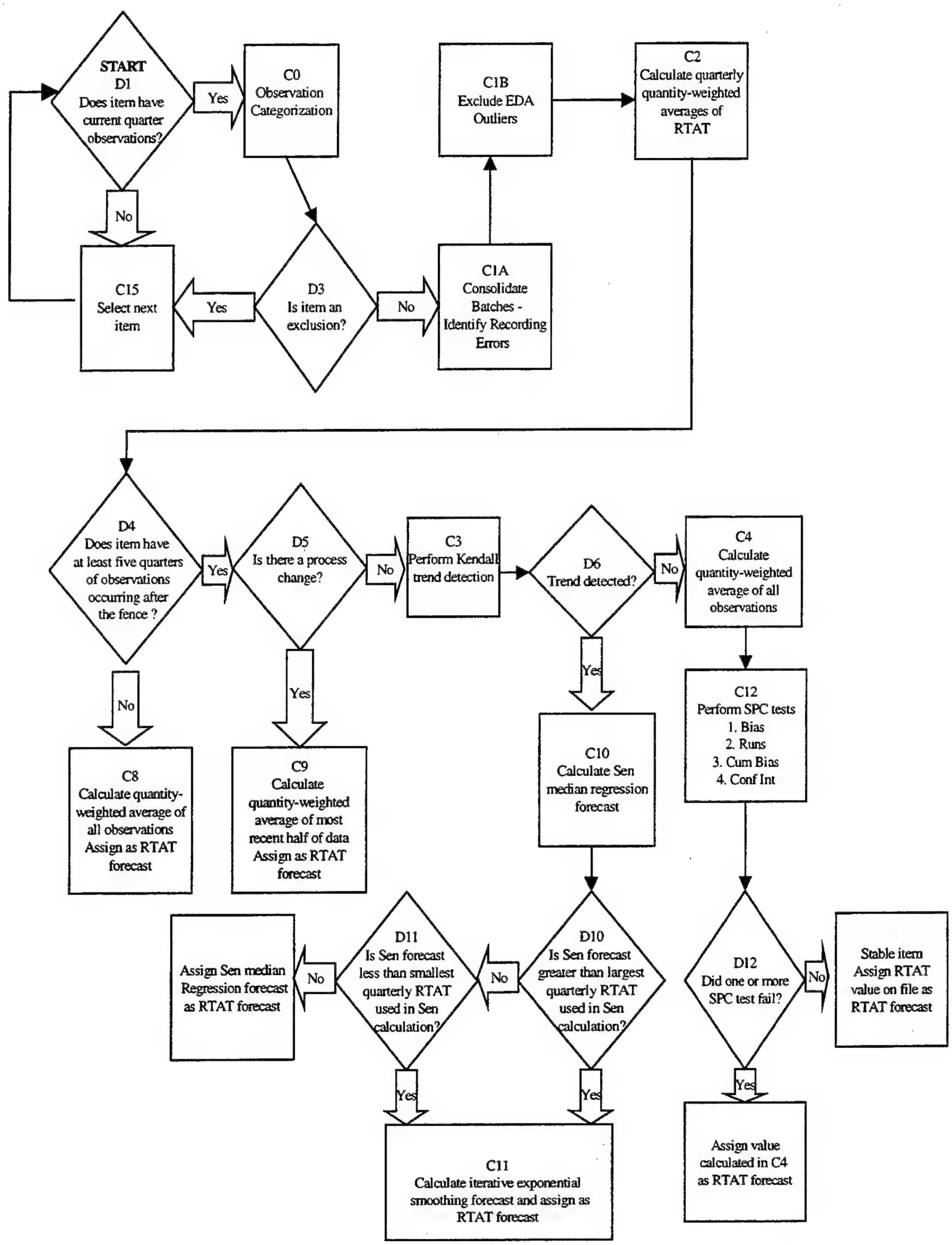

Figure 2.1: Flowchart of UICP Repair Turn-Around Time Forecast Model

B. MODEL DESCRIPTION

In this section, portions of the UICP RTAT forecast model are described. Discussion of a methodology, computation, or decision explicitly represented by a flowchart block from Figure 1 contains a reference to that block number. For example, Observation Categorization (C0) refers to block (C0) on the flowchart.

1. Observation Categorization (C0)

Current quarter repair observations must be available to run the model. Therefore, a new forecast will not be produced if there is no data from which to produce it. For each repairable item, only RTAT observations with repair completion dates occurring after a cut-off date (called the *fence*) are considered in RTAT forecast computations. The fence is used to demarcate the latest change in the distribution of RTAT as the repair process evolves across time. If current quarter observations are available for a particular repairable item (D1), that item is first checked against an *exception* file and a set of exception parameters; it is also checked against an *exclusion* file and a set of exclusion parameters. The exception and exclusion files list repairable items for which special management attention is mandated. If an item is determined to be an exception or exclusion, the exception or exclusion indicator is set. If an item's exclusion indicator is set, then no new RTAT forecast is computed. Forecasts for items identified by the program as exceptions are computed, but must be reviewed by item managers before being accepted.

2. Batch Consolidation (C1A)

A repairable item not identified as an exclusion and having current quarter observations is subject to a process called *batch consolidation.* Separate observations

that have identical repair completion dates, turn-around times (TAT), and designated overhaul points (DOP) are consolidated into a single observation, as illustrated by the following example:

Before batch consolidation:

Quantity	TAT observation[1]	Completion Date[2]	DOP
1	150	93014	Q24900
2	150	93014	Q24900

After batch consolidation:

Quantity	TAT observation	Completion Date	DOP
3	150	93014	Q24900

Following batch consolidation, all RTAT observations that are outside of an acceptance range are discarded from subsequent calculations. It is assumed that these observation values are caused by errors in data recording. At the time this thesis was written the maximum and minimum allowable values were 998 days and 4 days respectively (Jacoby, 1999).

3. Outlier Exclusion (C1B) and Computation of Quarterly Quantity-Weighted Average RTAT (C2)

If there are four or more (batch-consolidated) repair observations available for an item, outlier screening (C1B) is conducted. Observations identified as outliers at this stage are excluded from subsequent calculations.

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[1] TAT is measured in days.

[2] Dates are given in YYDDD format. For example, 93014 is 14 January, 1993.

Outliers are observations identified as lying outside of a range defined by quantities called the *Inner Fourth Upper* (IFU) and *Inner Fourth Lower* (IFL). These quantities are determined by first calculating the *fourth spread (FS)* (also known as the inter quartile range), which is the difference of the lower fourth (FL, the sample 25th percentile) from the upper fourth (FU, the sample 75th percentile). The upper and lower outlier cutoff values are given by IFU = FU + p*FS and IFL = FL – p*FS, where p is a program parameter. At the time this thesis was written $p = 1$ was used in the UICP RTAT forecast model (Jacoby, 1999). Although they are excluded from computations for the quarter in which they occur, outliers may be considered in future forecasts and are saved to a history file for review by item managers.

The following example illustrates the outlier identification process:

1. Set $p = 1$
2. *RTAT observations* (n *= 12) sorted from smallest to largest: 7, 10, 14, 15, 20, 23, 25, 29, 30, 49, 57, 66*
3. Lower Fourth (FL) = $(n*.25)^{th}$ observation = 3rd observation (RTAT = **14**)
4. Upper Fourth (FU) = $(n*.75)^{th}$ observation = 9th observation (RTAT = **30**)
5. Fourth Spread (FS) = FU – FL = 30 – 14 = **16**
6. IFL = FL – p*FS = 14 – 1*16 = **-2**
7. IFU = FU + p*FS = 30 + 1*16 = **46**
8. Identified outliers: RTAT = **49, 57, and 66**.

Following the outlier exclusion step, quantity-weighted averages of RTAT are computed by quarter, and the number of quarters that have repair observations for the item are determined (C2). Weights assigned in computing the quantity-weighted average of RTAT are the quantity of repairs completed for each repair observation.

4. Quantity-Weighted Average of All RTAT Data (C8)

The quantity-weighted average of all RTAT observations from the fence date to the last quarter for which data are available is adopted as the RTAT forecast whenever too few quarters of data are available to make a determination of a trend or process change in RTAT. Process change detection and trend detection are explained later in this section. The quantity-weighted average is adopted as the RTAT forecast provided that the following conditions are met:

- The item is not identified as an exclusion (D3)
- The item has four or more repair observations occurring after the fence
- There are fewer than five quarters of repair observation data occurring after the fence for the item (D4).

Suppose that a process change is determined to have occurred in the most recent half of six quarters of data. The fence is then reset to the first day of the quarter following the detected process change. The forecast for the following quarter is then a quantity-weighted average using only the last four quarters of data.

5. Process Change Detection (D5)

A *process change* is defined as an abrupt change in the distribution of repair times. For instance, if RTAT averages 100 days over several quarters, but then drops to thirty days over several quarters, a process change may have occurred. The UICP model requires that at least 5 quarters of repair observations be available for process change computations. Specifically, process change detection (D5) is conducted on any item that satisfies all of the following conditions:

- The item is not identified as an exclusion in step (D3)
- The item has four or more repair observations occurring after the fence
- The item has five or more quarters of repair observation data occurring after the fence (D4).

To determine if a process change has occurred, up to ten of the most recent quarterly RTAT averages are utilized in the manner described below:

Process Change Detection Algorithm

1. Assign as *A1* the average of the oldest half of the quarterly RTAT averages.
2. Assign as *A2* the average of the most recent half of the quarterly RTAT averages. If an odd number (n) of quarters of data are available after the fence, the average of the most recent quarterly averages is computed using the most recent $(n-1)/2+1$ quarters, and the average of the oldest quarterly RTAT averages is computed using the remaining quarters.
3. Assign as *Difference* the quantity $(A2 - A1)/\mathrm{Max}(A1, A2)$.
4. If the absolute value of *Difference* is greater than an adjustable parameter, then a process change is considered to have occurred.

The following example illustrates the process change detection procedure:

- *Difference* parameter = 0.15, fence = 1 July 1997
- Quarterly quantity-weighted averages of RTAT are shown in Table 2.1.
- *A1* = average of the older half of RTAT data = (56+39+49+55+67)/5 = **53.2**
- *A2* = average of the recent half of the data = (67+72+70+59+75)/5 = **68.6**
- *Difference* = $(A2 - A1)/\max(A2, A1)$ = (68.6 – 53.2)/68.6 = **0.224**
- Since 0.224 is greater than 0.15, a process change is assumed.

Table 2.1: Average RTAT Sorted By Quarter

Year Qtr	Avg RTAT
1997 Qtr 3	56
1997 Qtr 4	39
1998 Qtr 1	49
1998 Qtr 2	55
1998 Qtr 3	67
1998 Qtr 4	67
1999 Qtr 1	72
1999 Qtr 2	70
1999 Qtr 3	59
1999 Qtr 4	75

6. Quantity-Weighted Average of Most Recent Half of Data (C9)

The quantity-weighted RTAT average of the most recent half of the data is assigned as the candidate RTAT forecast if:

- The item is not identified as an exclusion in step (D3)
- A process change is detected in step (D5).

The fence is then reset to the first day of the most recent half of the data.

7. Kendall Trend Detection (C3)

Kendall trend detection is a rank correlation method used in the UICP RTAT forecast model to detect increasing and decreasing trends in repair times. It is based on Kendall's S statistic, which is calculated by subtracting the number of pairs (x, y) for which y is less than x from the number of pairs for which x is less than y. Here, x and y refer to quantity-weighted RTAT averages for quarters in which x occurs before y. Larger positive, or negative, values of S give stronger indications of an upward, or downward, trend across time. Values of Kendall's S are referred to probability tables (e.g. Kendall and Gibbons, 1990) to determine if the null hypothesis of no trend should be rejected.

Kendall trend detection (C3) is performed when:

- The item is not identified as an exclusion in step (D3)
- The item has four or more repair observations occurring after the fence
- The item has five or more quarters of repair observations occurring after the fence (D4).
- A process change is not detected in step (D5).

Kendall trend detection is conducted as follows:

Kendall Trend Detection Algorithm

1. Arrange quantity-weighted RTAT averages by quarter in reverse time order.
2. Assign to *QTRCENT* the number of quarters containing RTAT data for the item.
3. Set the first window size $W = 5$. The window size W defines the number of consecutive quarters of repair data, going back from the current quarter, over which trend detection will occur.
4. Compute Kendall's S using the formula:

$$S = \sum_{i=1}^{W-1} \sum_{j=i+1}^{W} (\mathit{if}\ (R_i > R_j)\ \mathit{then}\ 1, \mathit{else\ if}\ (R_i < R_j)\ \mathit{then} -1, \mathit{else}\ 0)$$

where R_1 represents most recent (current) quarterly average RTAT.

5. Use Table 2.2 to find upper (T_{plus}) and lower (T_{minus}) bounds on S.
6. The test is resolved as follows:
   - If ($S \leq T_{minus}$ or $S \geq T_{plus}$) then a trend has been detected.
   - If ($T_{minus} < S < T_{plus}$) then check *QTRCENT*.
   - If $W = QTRCENT$, then no trend has been detected – **Stop**.
   - If $W < QTRCENT$, set $W = W + 1$. Recompute S, and compare to the upper and lower bounds obtained from the Table 2.2.

- Continue incrementing W and recomputing S until either a trend is detected or $W = QTRCENT$.

Table 2.2: Bounds on Kendall's *S*

	$W = 5$	$W = 6$	$W = 7$	$W = 8$	$W = 9$	$W = 10$
T_{plus}	6	9	10	13	15	18
T_{minus}	-6	-9	-10	-13	-15	-18

If a trend is detected, the fence is set to the first day in the trend window. Setting the fence to this date will prevent the UICP forecasting tool from considering repair data with completion dates occurring before the period in which the trend was detected.

The following example illustrates the application of the Kendall trend detection procedure. Quantity-weighted RTAT averages to be used in the example are provided in Table 2.3:

Table 2.3: Average RTAT in Reverse Time Order

Year Qtr	Avg RTAT
1999 Qtr 4	75
1999 Qtr 3	69
1999 Qtr 2	70
1999 Qtr 1	72
1998 Qtr 4	67
1998 Qtr 3	58
1998 Qtr 2	55
1998 Qtr 1	49
1997 Qtr4	39
1997 Qtr 3	56

- Set $W = 5$. Since $W = 5$, only the most recent five quarterly averages are used in the calculation.

- Calculate S. A pairwise comparison is done between each of the RTAT values in the five-quarter window such that each quarterly RTAT is compared only to those quarterly RTAT values that occurred before it. Table 2.4 is an illustration of the results of such comparisons in a five-quarter window.

Table 2.4: Kendall Trend Detection Results – 5 Quarter Window

Index Year Qtr	Avg RTAT	$i = 1$	$i = 2$	$i = 3$	$i = 4$	
1) 1999 04	75	NC	NC	NC	NC	$j = 1$
2) 1999 03	69	1	NC	NC	NC	$j = 2$
3) 1999 02	70	1	-1	NC	NC	$j = 3$
4) 1999 01	72	1	-1	-1	NC	$j = 4$
5) 1998 04	67	1	1	1	1	$j = 5$
1 represents incrementing S			$W = 5$			
-1 represents decrementing S			$S = 4$			
NC in a block indicates that no comparison may be made between quarterly RTAT values represented by that block(RTAT i must occur before RTAT j in all comparisons)						

- $S = 4$, $W = 5$. In order for a trend to be detected in window size $W = 5$, S must be greater than or equal to 6, or less than or equal to negative six. A trend was not detected in this case.

- Since a trend is not detected, increment W to six.

- Calculate S. Table 2.5 is an illustration of the results of the calculation and comparisons for a six-quarter window.

- $S = 9$, which equals T_{plus} in a six quarter window. A positive or upward trend in RTAT is detected.

- Reset the fence to 1 July 1998 (the first day of the last quarter in the window).

Table 2.5: Kendall Trend Detection Results – 6 Quarter Window

Index Year Qtr.	Avg RTAT	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 5$	
1) 1999 04	75	NC	NC	NC	NC	NC	$j = 1$
2) 1999 03	69	1	NC	NC	NC	NC	$j = 2$
3) 1999 02	70	1	-1	NC	NC	NC	$j = 3$
4) 1999 01	72	1	-1	-1	NC	NC	$j = 4$
5) 1998 04	67	1	1	1	1	NC	$j = 5$
6) 1998 03	58	1	1	1	1	1	$j = 6$
1 represents incrementing S			$W = 6$				
(-1) represents decrementing S			$S = 9$				
NC in a block indicates that no comparison may be made between quarterly RTAT values represented by that block (RTAT i must occur before RTAT j in all comparisons)							

8. Sen Median Regression (C10)

Sen median regression RTAT forecasts are determined by computing a linear regression formula from the quarterly quantity-weighted averages of RTAT calculated in step (C2). Sen median regression allows a trend in repair times to be incorporated into RTAT forecasts. It is used under the following conditions:

- The item is not identified as an exclusion in step (D2)
- A trend is detected in step (D6).

To calculate the Sen median regression RTAT forecast, the final quantity W from the Kendall trend detection step (C3) is used:

Sen Median Regression Algorithm

1. Arrange the W quantity-weighted quarterly averages of RTAT in reverse time order $R_1, \ldots, R_W$, where R_w is the most recent (current) quarterly average. Let $\tilde{R}$ denote the median of these averages, and let $\tilde{q}$ denote the median of the numbers $\{1, 2, \ldots, W\}$.

2. Compute the slopes of the lines connecting each quarterly average RTAT to every other prior quarterly average RTAT:

   $$M_{ij} = \frac{R_j - R_i}{j - i}$$

   where: $i < j$

   Let $\tilde{M}$ denote the median of these slopes.

3. Compute the regression line's estimated intercept (β_0) using the formula

   $$\beta_0 = \tilde{R} - \tilde{M}\,\tilde{q}$$

4. Compute the Sen median regression RTAT forecast using the formula:

   $$\text{RTAT forecast} = \beta_0 + \tilde{M}\,W$$

If the forecast computed in this step is between the minimum (D11) and maximum (D10) quarterly quantity-weighted average RTAT value, assign it as the RTAT forecast. Otherwise, compute an iterative exponential smoothing forecast (C11), which is described below.

The following example illustrates the application of Sen median regression. Quantity-weighted RTAT averages to be used in the example are provided in Table 2.6:

Table 2.6: Data for Sen Median Regression Example

$W = 5$	
Quarter (*i* or *j*)	***R* (Quarterly Average RTAT)**
1	54
2	40
3	77
4	115
5 (current quarter)	139

1. The median quantity-weighted average of RTAT is $\tilde{R} = \mathbf{77}$, and the median quarter is $\tilde{q} = \mathbf{3}$.

2. Calculate the slopes of the lines connecting each quarterly average RTAT to each prior quarterly average RTAT, $M_{ij} = \dfrac{R_j - R_i}{j - i}$. The calculation results are listed in Table 2.7.

3. Calculate the median slope: $\tilde{M} = \dfrac{31+24}{2} = \mathbf{27.5}$

4. Calculate the regression line's estimated intercept: $\beta_0 = \tilde{R} - \tilde{M}\,\tilde{q} = 77 - 27.5(3) = \mathbf{-5.5}$

5. Calculate the RTAT forecast: forecast $= a + \tilde{M}\,W = -5.5 + 27.5(5) = \mathbf{132}$.

Table 2.7: RTAT Slopes ($M_{i,j}$)

R_i on rows, R_j on columns ($i < j$) (median bold)				
	$R_2 = 40$	$R_3 = 77$	$R_4 = 115$	$R_5 = 139$
$R_1 = 54$	-14	11.5	20.3	21.3
$R_2 = 40$		37	37.5	33
$R_3 = 77$			38	**31**
$R_4 = 115$				**24**

9. Iterative Exponential Smoothing (C11)

Iterative Exponential Smoothing (C11) is used when the forecast generated using Sen median regression is either greater than or less than all of the quantity-weighted quarterly averages of RTAT used in the forecast calculation (D10, D11). The smoothing weight has been coded as a program parameter and may be modified. Currently, the smoothing weight is $a = 0.40$.

To calculate the RTAT forecast using iterative exponential smoothing, the value for W obtained in the final step of the Kendall trend detection procedure (C3) is used. The candidate RTAT forecast value is determined by exponentially smoothing the most recent W quarterly averages of RTAT.

Algorithm for Iterative Exponential Smoothing

1. Let R_t denote the quantity-weighted RTAT average for quarter t, where $t = 1$ represents the first quarter used in calculating forecasts. Let $\hat{R}_t$ denote the RTAT forecast for quarter t. Define $\hat{R}_1 \equiv R_1$.

2. For $t = 2, \ldots$ recursively define $\hat{R}_t = aR_{t-1} + (1-a)\hat{R}_{t-1}$.

3. Round the final forecast to the nearest integer.

Table 2.8 illustrates the application of exponential smoothing:

Table 2.8: Exponential Smoothing Example

Parameters: a = .4, W = 5		
Quarter (t)	R_t **(Quarterly Average RTAT)**	$\hat{R}_t$ **(Forecast)**
1	54	54
2	40	(.4*40) + (.6*54) = 48.4
3	77	(.4*77) + (.6*48.4) = 59.6
4	115	(.4*115) + (.6*59.6) = 82
5 (current quarter)	139	(.4*139) + (.6*82) = 104.8

Assign 105 as the candidate RTAT forecast for quarter 6 (.5 rounding is used only on the final result).

10. Quantity-Weighted Average of RTAT Observations Occurring After the Fence (C4)

The quantity-weighted average of all RTAT observations occurring after the fence (C4) will be used as the forecast value under the following conditions:

- The item is not identified as an exclusion in step (D3)
- The item has four or more repair observations occurring after the fence
- There are five or more quarters of repair observations occurring after the fence for the item (D4)
- A process change is not detected in step (D5)
- A trend is not detected in step (D6).

When the quantity-weighted average is calculated, four Statistical Process Control (SPC) tests are conducted (C12). At least one of the four tests must produce a failure in order for the quantity-weighted average to be assigned as the candidate RTAT forecast. If none of the four SPC tests produces a failure, the item's RTAT is considered stable and the RTAT forecast is assigned the same value as last quarter's forecast (the file RTAT).

Whenever RTAT is determined to be stable, the quantity-weighted average of all observations is assigned as the forecast tracking mean (FTM) for the quarter in which it is produced. The term "SPC quarter" refers to the number of successive quarters in which RTAT is considered stable for an item. For instance, if RTAT is considered stable for three consecutive quarters, three FTMs will be available for use in the SPC calculations corresponding to quarters one, two, and three. The four SPC tests are described in the following subsection.

11. Statistical Process Control Tests (C12)

a. SPC Test 1 - Bias Test

Bias percent is calculated using the formula:

$$\text{Bias percent} = \frac{(\text{quantity - weighted average of all RTAT observations} - \text{file RTAT})}{\text{file RTAT}}$$

where: file RTAT = previous quarter RTAT forecast

If Bias percent is less than or equal to lower bias percent or greater than or equal to upper bias percent, then the test fails. Lower and upper bias percent are coded as program parameters and may be modified. If the bias test fails, the quantity-weighted average of all observations after the fence (C4) is assigned as the candidate RTAT forecast.

The following example illustrates the application of the bias test:

Bias percent parameters are -.15 and .15

SPC QTR	FTM	file RTAT	bias percent
1	82.8	90.9	-.09
2	74.3	90.9	-.18 (Bias Test failure)

b. SPC Test 2 - Runs Test

The “runs test” uses the Bias percent value calculated in the bias test described in section 11(a). Adjustable parameters called “runs parameters” are used to determine when to increment, decrement, or reset a counter called the file mean counter (MC). When the file MC is equal to an upper or lower bound determined by MC parameters, a test failure occurs.

The file MC is incremented, decremented or reset after each bias percent calculation based on the following rules:

- Reset file MC to zero when
  1) Bias percent is within the runs parameters and
  2) Bias percent has the opposite sign as the file MC
- Reset file MC to 1 (if bias percent is positive) or –1 (if bias percent is negative) when
  1) Bias percent is outside of the runs parameters and
  2) Bias percent has the opposite sign as the file MC
- Increment file MC when
  1) Bias percent is greater than or equal to the upper runs parameter and
  2) Current file MC is positive or zero
- Decrement file MC when
  1) Bias percent is less than or equal to the lower runs parameter and
  2) Current file MC is negative or zero

If the bias test does not produce a test failure, but the runs test does, the quantity-weighted average RTAT of all observations is assigned as the candidate RTAT forecast.

Table 2.9 illustrates the application of the runs test:

Table 2.9: Runs Test Example

runs parameters are -.05 and .05, and mean counter parameters are –3 and 3				
SPC QTR	**file MC**	**Bias Percent**	**MC adjustment**	**New file MC**
1	0	-.09	-1	-1
2	-1	-.04	Reset to 0	0
3	0	-.09	-1	-1
4	-1	.18	Reset to 1	1
5	1	.18	+1	2
6	2	.02	0	2
7	2	.18	+1	3 (test failure)

c. SPC Test 3 - Cumulative Bias Test

There must be at least 3 SPC quarters to perform the cumulative bias test. This test also uses the bias percent values calculated in the bias test. A *cumulative average bias percentage* is computed by dividing the cumulative bias percentage by the number of SPC quarters. If the cumulative average bias percentage is outside of bounds determined by cumulative average bias parameters, the test produces a failure. If the cumulative bias test results in the first SPC test failure, the quantity-weighted average RTAT of all observations is assigned as the candidate RTAT forecast.

Table 2.10 illustrates the application of the cumulative bias test:

Table 2.10: Cumulative Bias Test Example

Cumulative average bias parameters are -.1 and .1			
SPC QTR	**Bias %**	**cum bias %**	**Cum average bias %**
1	-.09	-.09	
2	-.09	-.18	
3	-.18	-.36	-.12 (test failure)

d. SPC Test 4 – Confidence Interval Test

There must be at least 3 SPC quarters available to perform the confidence interval test. Either a 90 or 95 percent confidence interval may be specified. The

confidence interval is based on the Student t Distribution and the standard error of quarterly forecast tracking means. A failure occurs when the file RTAT (last quarter's forecast) is outside of this confidence interval. If the confidence interval test results in the first SPC test failure, then the quantity-weighted average RTAT of all observations is assigned as the RTAT forecast.

The following formulas are used in the confidence interval test:

Lower Confidence Interval Limit = current quarter FTM – t value SD*

*Upper Confidence Interval Limit = current quarter FTM + t value*SD*

$$SD = \sqrt{\frac{\sum_{i}^{SPC\ quarters} (FTM_i - \overline{FTM})^2}{SPC\ quarters}}$$

The following example illustrates the confidence interval test:

1. assume that a 90% confidence interval will be used, SPC quarters = 3, and file RTAT = 90.9 (file RTAT is last quarter's RTAT forecast)

2. Average FTM = (82.8 + 83.0 + 74.3)/3 = 80.0

3. SD = $\sqrt{\frac{(82.8-80.0)^2 + (83.0-80.0)^2 + (74.3-80.0)^2}{3}} = 4.06$

4. Lower Confidence Interval Limit = 74.3 – 2.92*4.06 = 62.4

5. Upper Confidence Interval Limit = 74.3 + 2.92*4.06 = 86.2

6. A failure occurs because 90.9 is outside of the confidence interval limits.

12. Automatic Update

The UICP RTAT forecast model contains several tests used to identify items for item manager review. RTAT values for items identified for review are not automatically updated by the UICP forecast model. The tests evaluate the need for review based on the

magnitude of the differences between the previous quarter's RTAT forecast and the candidate RTAT forecast, quarterly item demand, and repairable item cost. Review is also mandatory for all items which are listed in an exception file or which meet exception parameters.

If any of the automatic update tests fail, then the UICP RTAT forecast model prompts for item manager review. If none of the automatic update tests indicate that the item manager review is necessary, then the model will update the file RTAT with the candidate RTAT forecast.

III. DATA DESCRIPTION

In this chapter, the database provided by NAVICP-Phil is described. Because NAVICP manages several thousand repairable items, data for all items could not be analyzed within the scope of this thesis. Therefore, a subset of 15 NAVICP-Phil managed items is chosen. That subset is described in this chapter.

The UICP RTAT forecast model produces separate forecasts for items identified by a National Item Identification Number (NIIN). Quantities used in computing the forecasts are the repair turn-around times (RTATs) of completed repair transactions and the completion dates. Assumptions of the UICP RTAT forecast model implied by using only these data elements are addressed in Section B.

A. DATA

The data used to conduct the analyses described in this thesis consist of individual repairs completed in calendar years 1996, 1997, and 1998 on repairable items that support naval aviation assets. The data were provided by NAVICP-Phil. Approximately 130,000 observations were available for each of the three calendar years. Appendix B gives a detailed description of each of the 13 fields that comprise the NAVICP-Phil database.

In this thesis a subset consisting of 15 items from the 11,759 repairable item NAVICP-Phil database is identified for most of the analyses conducted (seven additional items are used in regression analyses conducted in Chapter IV). The first ten items of the 15 item subset are selected to meet the following criteria:

- The items have at least ten repair observations available in each of the twelve quarters spanning the three-year period from 1 January 1996 through 31 December 1998.

- The items represent high-dollar value repairable activities, with respect to the quantity repaired and the per-unit value of the items.

The criteria are chosen to ensure that analysis is performed on items that represent a large proportion of the entire database with regard to total dollar value, and have enough repair observations occurring in each quarter to permit meaningful analysis. The first ten items are chosen based on extended standard price, which is the product of the per-unit price of the item and the total quantity of the item repaired. The ten items with the highest extended standard prices over the three-year period from 1996 through 1998 are selected.

The remaining five items are chosen based on quantity of repairs only. They are those items having the highest quantities of repairs completed over the three-year period, ignoring those items already selected based on extended standard price. The items contained in the 15 item subset are listed and described in Appendix C. Additional information regarding quantities repaired, the products of quantity repaired and repair turn-around time, and extended price is also summarized for the fifteen items in Appendix C.

B. ISSUES CONCERNING MEASUREMENT OF RTAT

The UICP RTAT forecast model produces forecasts entirely through examination of individual repair turn-around times of completed repair transactions. Information on repairs that are ongoing but not completed is not incorporated into prediction methodologies. The underlying model assumption is that repair turn-around times of items inducted into the repair system may be predicted entirely by examining the statistical properties of completed repairs. In this section, the implications of this assumption are explained.

Let t refer to a fixed point in time; let $R_{t,C}$ denote the RTAT of a repair transaction completed at time t; and let $R_{t,I}$ denote the RTAT of a repair transaction inducted at time t. The model assumption states, in essence that $R_{t,C}$ and $R_{t,I}$ have the same probability distribution; in other words, the distribution of RTAT is "time reversible." This assumption, however, is not valid in general, and the conditions under which it is reasonable are rather restrictive. In fact, the distributions of $R_{t,C}$ and $R_{t,I}$ can be quite different even when the underlying repair process is stationary with respect to time. In this thesis, the repair time of an item completed in a particular quarter will be referred to as a *completion RTAT*, and the repair time of an item sent out for repair will be referred to as an *induction RTAT* relative to that quarter.

The simplest example of a situation in which time reversibility exists is the classical M/M/1 queue. A comprehensive discussion of M/M/1 and other queueing systems can be found in Baccelli and Bremaud (1994). In an M/M/1 queue, both the times between arrivals to a single server system and the service times themselves are distributed exponentially, independently of each other but with possibly different parameters.

The assumption of exponentially distributed repair times is often regarded as unrealistic, because the "memoryless" property of the exponential distribution implies that the time needed to complete a repair is probabilistically unaffected by the length of time that the item has already spent on repair. The assumption of exponentially distributed interarrival times is equivalent to items entering the repair queue according to a Poisson process. It can be shown that time reversibility also holds if repairs follow a general probability distribution that is stationary with respect to time, provided that

interarrivals are exponentially distributed and the system has been in operation for a long time. This type of queueing system is known as the M/G/1 queue. (Ross, 1997)

There are two respects in which NAVICP repair times violate the conditions needed for time reversibility: nonstationarity of repair times and nonrandomness of repair arrivals. These issues are discussed separately in the subsections that follow.

1. Non-stationarity of Repair Turn-Around Time Distributions

Repair time distributions for NAVICP managed repairable items are not inherently stationary; indeed, an important purpose of the UICP RTAT forecast model is to detect changes in RTAT distributions. The UICP RTAT forecast model uses two methodologies for detecting departures from stationarity – Kendall trend detection and process change detection, which are described in Chapter II.

To illustrate how non-stationarity effects time reversibility, suppose that a problem in the repair system occurring at a point in time causes repair times that previously were stable to increase significantly. It is conceivable that none of the completion RTATs received in the same quarter were affected by the problem. The distribution of completion RTATs in that quarter will be different (it will have a smaller mean) than the distribution of induction RTATs in that same quarter. Since the UICP RTAT forecasting model considers only completion RTATs in its methodologies, the forecasts for future quarters will underestimate the true mean repair time until repairs affected by the problem enter the data stream and dominate the forecasts. A latency period will be required before either the Kendall trend detection or process change detection procedures that are integrated into the UICP RTAT forecast model are able to

identify the change. Until the change in distribution is detected, past data with low completion RTAT values will influence predictions.

A similar situation exists for decreasing trends in repair time. Suppose that a problem resulting in unusually long repair times is corrected. As the system flushes backlog, large completion RTAT values may be observed. These large completion RTAT values will affect forecasts until enough time passes for the forecast method to detect the changed circumstances.

Both of the above examples illustrate that forecasts based on completion RTAT values lag behind changes in the distributions of repair times. Induction RTAT values, by contrast, reflect the state of the repair system as it changes over time. However, a drawback to using induction RTAT values in forecasting is the fact that an item inducted for repair in a given quarter may not be completed by the time forecasts are made. This is the phenomenon known as *censoring*, which requires specialized handling in statistical estimation.

2. The Effect of Scheduling on Repair Turn-Around Time Distributions

The second violation of the time reversibility assumption in the UICP RTAT forecast model is due to nonrandom system arrivals. Arrivals to the repair systems monitored by NAVICP are often scheduled and arrive at overhaul points in batches.

When items are inducted into the repair system in a nonrandom manner, the distribution of completion RTATs may appear nonstationary even when the distribution of repair time is stationary. For example, if all items are inducted into the repair system on 1 January of a given year, completion RTATs occurring in later quarters will certainly have longer RTATs than those occurring earlier, and will give the appearance of an

increasing trend in repair times. Although this is an extreme example, it serves to illustrate the point that scheduling affects the distribution of observed completion RTATs. This problem may be minimized by scheduling repairs evenly across time, to the extent that doing so is practical.

Figure 3.1 shows the differences between completion RTATs and induction RTATs for one repairable item.

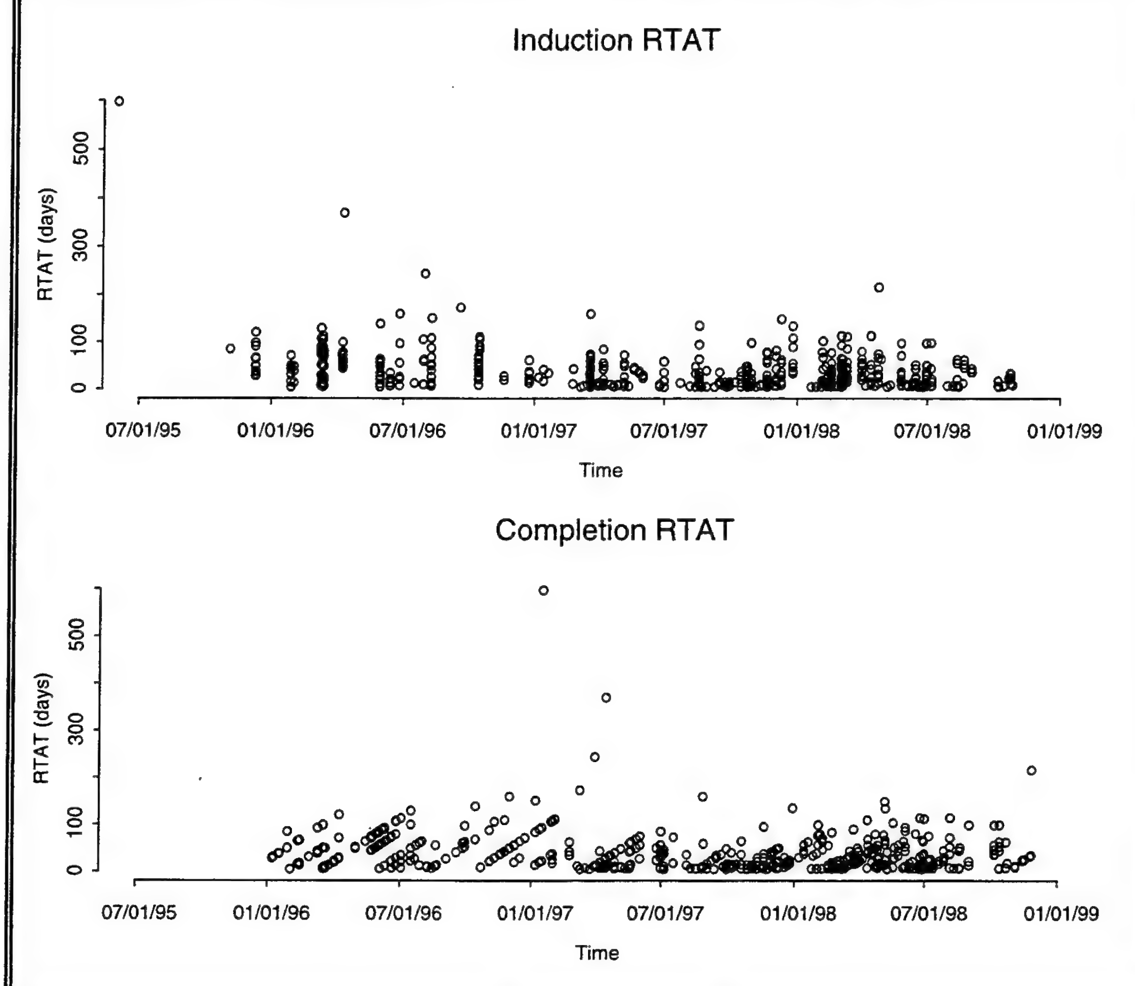

Figure 3.1: Differences in Distributions of Completion RTAT and Induction RTAT for Navigational Unit 1, NIIN 01-054-3776

It is apparent from this discussion, that assuming time reversibility and consequently, using completion RTATs in RTAT forecasting has obvious shortcomings.

Despite these shortcomings, the approach is attractive because of its simplicity. Considering only completed repairs enables forecasters to make predictions using fairly simple techniques, and requires data collection for a small set of variables – namely, repair completion quarter and RTAT of completed repairs. Incorporating a completion RTAT approach also eliminates the requirement to address censoring problems that are likely to occur when using induction RTATs. In this thesis, the UICP convention of using completion RTATs will be adopted for assessing model performance and in comparing the UICP RTAT forecast model to alternative time series forecast techniques.

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IV. UICP RTAT FORECAST MODEL ANALYSIS

In this chapter, the UICP RTAT forecast model accuracy is evaluated, and the model is compared to alternative forecasting techniques. The predictive power of variables not considered by the model is also assessed.

A. OUTLIER EXCLUSION

The UICP RTAT forecast model, described in Chapter II, provides for the exclusion of extremely high and low RTAT observations when calculating quarterly, quantity-weighted RTAT averages. Extreme observations have undue influence on these averages and consequently on forecasts that depend upon them. A dramatic change to an RTAT forecast may result in unnecessary, costly adjustments to inventory quantities and repair schedules. But, excluding a large share of observations as outliers may impart bias to RTAT forecasts if the exclusions are disproportionate on one end of a distribution.

RTAT variance computations are also affected by outlier exclusion. Removing outlying observations will necessarily reduce measured variance because, by definition, outlying observations are greater distances from the mean and therefore contribute greater squared differences than non-outlying observations. RTAT variance is one of the variables used to determine *safety stock* levels of items held in inventory to prevent shortages. When repair time, procurement time, or demand is greater than their estimated expected values, requisitions are filled by issuing items from safety stock. Since RTAT variance partially determines safety stock quantities, artificially reducing it by removing large numbers of outlying observations could result in more out-of-stock situations and poor service to requisitioning customers.

In exploratory data analysis, *boxplots* are often used to provide a visual description of the location, spread, skewness, tail length, and outlying values in a distribution of data. Quantities that determine the boundaries of the box, the Lower Fourth (25^{th} percentile) and the Upper Fourth (75^{th} percentile), cover fifty percent of the data range. Together with the Fourth Spread, which is the difference of the Lower Fourth from the Upper Fourth, these quantities can be used to develop simple and robust rules for identifying outliers. The following lower and upper outlier cutoffs are often suggested:

$$\text{Lower Outlier Cutoff} = \text{Lower Fourth} - 1.5 * \text{Fourth Spread}$$
$$\text{Upper Outlier Cutoff} = \text{Upper Fourth} + 1.5 * \text{Fourth Spread}$$

Data values that fall above the Upper Outlier Cutoff or below the Lower Outlier Cutoff are regarded as outliers (Hoaglin, Mosteller, and Tukey, 1983). In the UICP RTAT forecast model the same outlier identification rule is used with the exception that the fourth spread is multiplied by 1.0 instead of 1.5.

In concept, an outlier signifies a magnitude of observation that is expected to occur infrequently under usual conditions. For instance, under the standard normal distribution, the population fourths are –0.6745 and 0.6745, the Fourth Spread is 1.349, and the outlier cutoffs using a multiplier of 1.5 are ±2.698. The probability that a standard normal random variable falls in the outlier region is only 0.7%, or about 7 out of every 1000 independent observations. Similarly for any symmetric distribution with light tails, outliers are expected to occur infrequently under this rule, and the frequencies of high and low outliers should be about the same. In the case of the uniform distribution no outliers would be observed in a sufficiently large sample because the outlier boundaries

would exceed the limits of the distribution. However, distributions having heavier tails can be expected to produce more outliers, and distributions that are skewed may result in outlier production that is higher on either the high or the low side. To illustrate this point, Table 4.1 shows the results of applying the boxplot outlier identification method to an exponential distribution having mean = 5 and a Gamma distribution having mean = 0.2 (shape parameter = 0.2, rate = 1). Histograms of these distributions are shown in Figure 4.1 and provide visual indications of skewness and tail thickness (Hoaglin, Mosteller, and Tukey, 1983).

Table 4.1: Outlier Identification in Exponential and Gamma Distributions

Outlier parameter = 1.5				
Distribution	**Upper Cutoff**	**Lower Cutoff**	**Probability of a High Outlier**	**Probability of a Low Outlier**
Exponential (mean = 5)	15.17	-6.80	.048	0
Gamma (mean = .2)	0.45	-0.27	.135	0

Table 4.1 shows the upper and lower boxplot outlier cutoffs for two skewed distributions and the probabilities that individual observations are outliers under boxplot outlier criteria. An outlier parameter value of 1.5 is used to multiply fourth spread in upper and lower cutoff calculations.

Table 4.1 shows that the probability of falling in the lower outlier region under either distribution is zero. Similarly, under either distribution the probability of falling in the upper outlier region is high compared to a normal distribution.

For several of the fifteen repairable items identified for analysis, the distributions of RTAT appear to be similar to the exponential and gamma distributions depicted in Figure 4.1. Many are highly skewed and have thick right tails. Figure 4.2 shows the histogram of RTAT for the Inertial Navigation Unit. The histogram for this item is similar to those for most of the 15 repairable items.

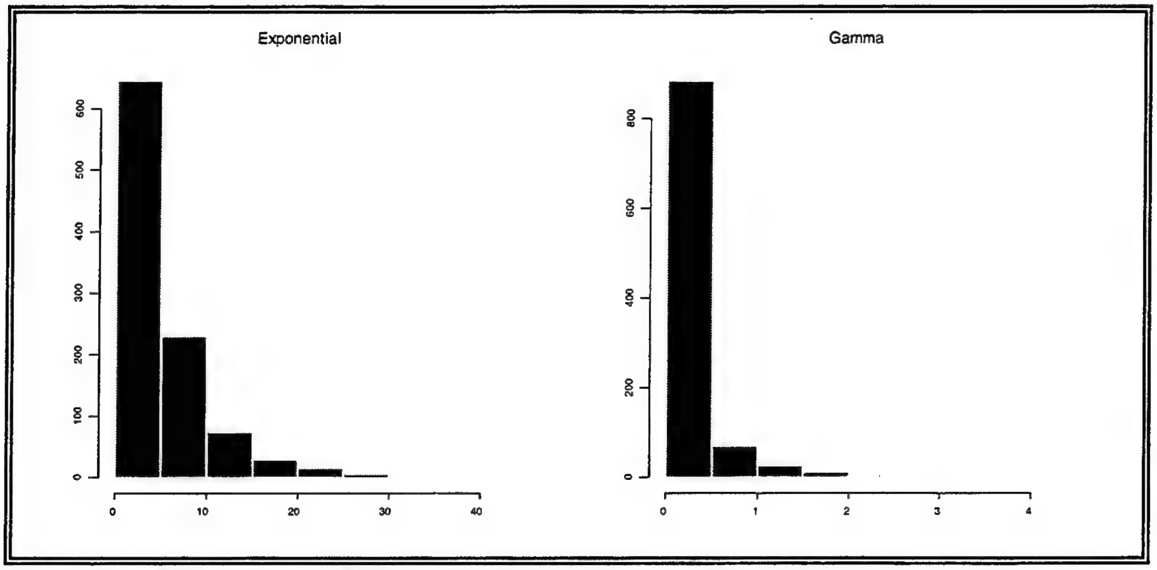

Figure 4.1: Histograms of Exponential and Gamma Distributions

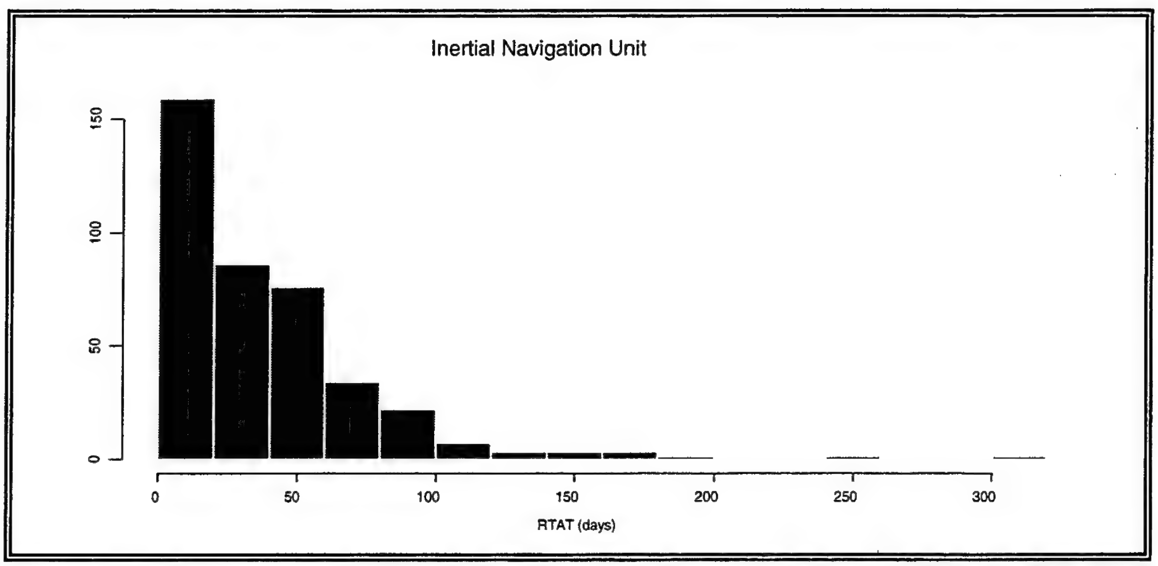

Figure 4.2: Histogram of RTAT for Inertial Navigation Unit, NIIN 01-387-0348. RTAT is measured in days.

High positive skewness results in identification of more high outliers than low, while heavy tails can result in large numbers of observations identified as outliers on either or both sides of the distribution. Table 4.2 provides numbers and percentages of high and low outliers identified for all 15 repairable items. For most items, large percentages of observations are identified as high outliers, and in all instances, more high

observations are identified as outliers than low ones. In 10 of the 15 items, the lower outlier cutoff is less than zero.

Table 4.2: Numbers and Percentages of Observations Excluded as Outliers by the UICP RTAT Forecast Model

Outlier parameter = 1							
NIIN	Upper Cutoff (IFU)	Lower Cutoff (IFL)	High Outliers	Percentage High	Low Outliers	Percentage Low	Total Observations
01-054-3776	96.75	-31.50	33	7%	0	0%	461
01-387-0348	95.00	-31.00	23	6%	0	0%	396
01-300-0940	81.75	4.50	29	10%	2	1%	297
01-011-0855	367.50	-146.25	34	4%	0	0%	863
01-351-3373	246.25	-91.25	123	16%	0	0%	757
01-343-7026	125.00	-22.00	156	17%	0	0%	903
01-316-3474	131.00	35.00	60	14%	14	3%	423
01-154-2794	146.00	-61.00	87	16%	0	0%	541
00-928-0072	105.00	0.00	115	13%	0	0%	911
00-887-1944	154.00	34.00	80	18%	6	1%	449
01-141-2735	70.00	-2.00	67	10%	0	0%	672
00-165-5838	64.00	-2.00	142	14%	0	0%	1027
00-411-6264	174.00	39.00	11	6%	3	2%	180
01-062-5846	454.00	-200.00	151	13%	0	0%	1168
01-139-7177	135.00	-13.50	50	19%	0	0%	267
Totals			**1161**	**12.46%**	**25**	**0.27%**	**9315**

Table 4.2 shows the numbers and percentages of observations excluded by the UICP RTAT forecast model outlier exclusion criteria. An outlier parameter of 1 is used to multiply fourth spread in upper and lower cutoff calculations.

It is apparent from this discussion that the frequency and placement of outliers excluded by the UICP RTAT forecast model are highly influenced by the shape of the distribution. Repair time distributions are highly positively skewed for most repairable items. The distributions of many items also have heavy right tails. In distributions exhibiting these characteristics, two undesirable results with respect to RTAT forecasting can occur:

1. More high observations than low will be excluded, which imparts negative bias to forecasts.

2. Measured variance will be much lower than actual variance.

Boxplot and the UICP RTAT forecast model outlier criteria may be useful for identifying observations that require special attention in exploratory data analysis. However, automatically excluding items identified by the criteria may lead to problems in RTAT forecasting. Since forecasts are based on quarterly RTAT averages, the model will tend to under-forecast average RTAT. This under-forecasting will occur both for items that have fairly stationary repair time distributions and those that do not. Items that have non-stationary repair time distributions may experience dampening of forecasts due to the exclusion of large proportions of high observations. Even without outlier exclusion dampening occurs due to the reverse-time orientation of completion RTATs. This characteristic lag effect was discussed in Chapter III.

B. RTAT UICP FORECAST MODEL PERFORMANCE

In this section, the calculations used in measuring forecast accuracy are defined, the accuracy of the UICP model is measured, and the performance of the UICP RTAT forecast model is compared to the performance of three simple alternative time series forecasting techniques.

1. Measuring Forecast Accuracy

> "Forecasting is probably going to be incorrect, so it is useful to predict the degree of inaccuracy." (Tersine, 1994)

By comparing the accuracy of different forecasting techniques with actual observations from the same periods, the performance of those techniques can be contrasted. Forecast accuracy is often measured using deviation and bias. Deviation measures the differences between forecasts and actual observations, while bias measures the tendency to consistently over- or under-forecast. Two measures of deviation are considered here. They are mean absolute deviation (MAD) and mean absolute

percentage deviation (MAPD). MAD is obtained by dividing the number of observations into the sum of absolute deviations:

$$\text{MAD} = \frac{\sum_{i=1}^{n} \left| Y_i - \hat{Y}_i \right|}{n}$$

where: $\hat{Y}_i$ = RTAT forecast for quarter i

Y_i = actual quantity-weighted average RTAT in quarter i

n = number of quarters of RTAT forecasts

$\left| Y_i - \hat{Y}_i \right|$ = absolute deviation or absolute forecast error

The formula for MAPD is similar, but based on percentage differences:

$$\text{MAPD} = \frac{100\% \times \sum_{i=1}^{n} \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right|}{n}$$

Two measures of bias are also calculated: mean error (ME), and mean percentage error (MPE). Their formulas are similar to the formulas for deviation, but are based on differences and percentage differences instead of absolute differences and absolute percentage differences respectively:

$$\text{ME} = \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)}{n}$$

$$\text{MPE} = \frac{100\% \times \sum_{i=1}^{n} (\frac{Y_i - \hat{Y}_i}{Y_i})}{n}.$$

Because MAPD and MPE are based on percentage differences instead of raw values they are not affected by scale. Therefore, MAPD and MPE will be used to measure forecast deviation and bias in this analysis. (Tersine, 1994)

2. Accuracy of the UICP RTAT Forecast Model

Accuracy is determined by comparing RTAT forecasts produced by the UICP RTAT forecast model to actual quarterly quantity-weighted average RTAT values from 1996 through 1998. Twelve quarters of repair observation data are available for each of the 15 items evaluated. Forecasts are produced for quarters six through twelve and compared to actual quarterly quantity-weighted averages of RTAT to determine accuracy. Because individual RTAT observation values less than four or greater than 998 are considered recording errors, they are not used in calculating quarterly quantity-weighted average RTAT values.

Measurements of deviation and bias of UICP model forecasts for each of the 15 repairable items studied are shown in Tables 4.3 and 4.4. Tables 4.3 and 4.4 also contain deviation and bias measures for alternative forcasting methodologies that will be discussed in later subsections.

Mean absolute percentage deviation of UICP model forecasts ranges from 21% to over 64% in the 15 items analyzed, indicating significant differences between RTAT forecasts and observed RTAT values. In most items considerable negative bias exists. For four items (NIINs 01-351-3373, 01-343-7026, 00-165-5838, 01-062-5846) RTAT is under-forecast in all seven quarters for which predictions are computed. These results demonstrate that applying the outlier exclusion criteria can produce RTAT forecasts that are systematically low.

Table 4.3: Evaluation of UICP RTAT Forecast Model Accuracy Using Mean Absolute Percentage Deviation (MAPD)

NIIN	Repair Quantity	UICP Model (Outlier parameter = 1)	Previous Quarter RTAT	Four Quarter Moving Average	Exponential Smooth (a=.3)	UICP Model (log transform) Outlier criteria off	UICP Model (log transform) Outlier parameter = 1
01-054-3776	1095	29.56	37.58	62.73	46.90	30.84	31.06
01-387-0348	720	21.13	18.21	40.51	44.28	21.81	21.14
01-300-0940	356	30.54	32.79	24.87	24.83	36.07	33.60
01-011-0855	1153	31.67	25.84	26.28	23.87	39.96	39.96
01-351-3373	932	36.54	22.94	26.43	28.97	57.98	59.51
01-343-7026	1185	64.62	27.77	22.77	24.51	54.99	65.05
01-316-3474	507	34.16	43.26	30.33	33.15	31.67	33.47
01-154-2794	633	52.93	104.87	88.40	83.50	47.93	53.3
00-928-0072	1779	30.41	94.03	46.24	45.52	44.34	38.01
00-887-1944	493	38.89	47.14	56.91	55.08	43.52	40.11
01-141-2735	2905	39.84	65.23	45.41	43.60	36.15	34.28
00-165-5838	2364	54.00	25.24	17.69	22.40	36.89	52.67
00-411-6264	1427	38.03	32.53	40.56	35.40	57.15	55.45
01-062-5846	1390	62.72	49.88	34.20	36.02	62.54	62.54
01-139-7177	1231	57.04	81.70	82.80	63.50	50.04	49.04
Quantity Weighted Average		**43.19**	**49.22**	**41.35**	**39.17**	**43.84**	**45.59**

Outlier parameter is the multiplier applied to the Fourth Spread to determine upper and lower outlier limits.

Table 4.4: Evaluation of UICP RTAT Forecast Bias Using Mean Percentage Error (MPE)

NIIN	Repair Quantity	UICP Model (Outlier parameter = 1)	Previous Quarter RTAT	Four Quarter Moving Average	Exponential Smooth (*a*=.3)	UICP Model (log transform) Outlier criteria off	UICP Model (log transform) Outlier parameter = 1
01-054-3776	1095	8.44	24.87	47.00	46.36	-25.48	-22.04
01-387-0348	720	5.30	2.35	26.34	39.15	-18.99	-16.00
01-300-0940	356	-23.17	6.01	-1.19	-0.08	-20.86	-26.04
01-011-0855	1153	-17.72	-0.82	-2.42	-7.66	-38.82	-38.82
01-351-3373	932	-36.54	-5.35	-0.68	9.45	-57.98	-59.51
01-343-7026	1185	-64.62	-3.55	-20.98	-24.10	-54.99	-65.05
01-316-3474	507	-14.65	-3.45	-5.64	3.03	-10.85	-13.90
01-154-2794	633	-39.26	55.47	42.54	31.33	-40.99	-46.36
00-928-0072	1779	-18.32	59.87	33.76	29.77	2.69	-2.84
00-887-1944	493	-27.98	26.47	28.31	24.51	-3.06	-26.60
01-141-2735	2905	3.80	32.72	19.71	15.49	8.25	-2.34
00-165-5838	2364	-54.00	-10.34	-16.96	-21.81	-36.89	-52.67
00-411-6264	1427	19.46	12.02	21.88	17.52	32.88	33.84
01-062-5846	1390	-62.72	-6.80	-21.75	-21.24	-62.54	-62.54
01-139-7177	1231	17.44	62.22	70.34	62.35	19.41	20.41
Quantity Weighted Average		**-19.78**	**18.09**	**13.46**	**11.14**	**-17.64**	**-23.20**

Outlier parameter is the multiplier applied to the Fourth Spread to determine upper and lower outlier limits.

Graphical representations of forecasts and repair time distributions for two different items (NIINs 01-343-7026 and 00-411-6264) are shown in Figure 4.3. For the first item depicted in Figure 4.3, the Servocylinder, F/A-18, RTAT forecasts relative to observations of quarterly quantity-weighted average RTAT are consistently low. Quarterly RTAT distributions for the Servocylinder, F/A-18 are representative of the distributions for most items in which RTAT is consistently under forecast. High positive skewness and heavy right tails are apparent in all quarterly RTAT distributions for this item. RTAT does not appear to exhibit any significant trend until the last two quarters. For the second item depicted in Figure 4.3, the Nozzle, Turbine Engine, it is apparent that the UICP RTAT forecast model does not consistently under-forecast RTAT. The location of the median relative to mean in each quarterly boxplot indicates that in many quarters significant skewness does not exist. Results of applying the outlier criteria to data for this item, shown in Table 4.2, confirm that skewness and heavy-tailedness are minimal. Only 6% of high observations were excluded as outliers, while 2% of low observations were excluded. The considerable upward trend in RTAT experienced in 1997 followed immediately by an even steeper downward trend in 1998 is also of interest. It is apparent from Figure 4.3 that UICP RTAT forecasts lag both of these trends.

These analyses demonstrate that the outlier criterion employed by the model imparts significant bias to RTAT forecasts. In particular, negative bias is most apparent in items that have highly positive skewed RTAT distributions and regular occurrence of relatively high RTAT observation values.

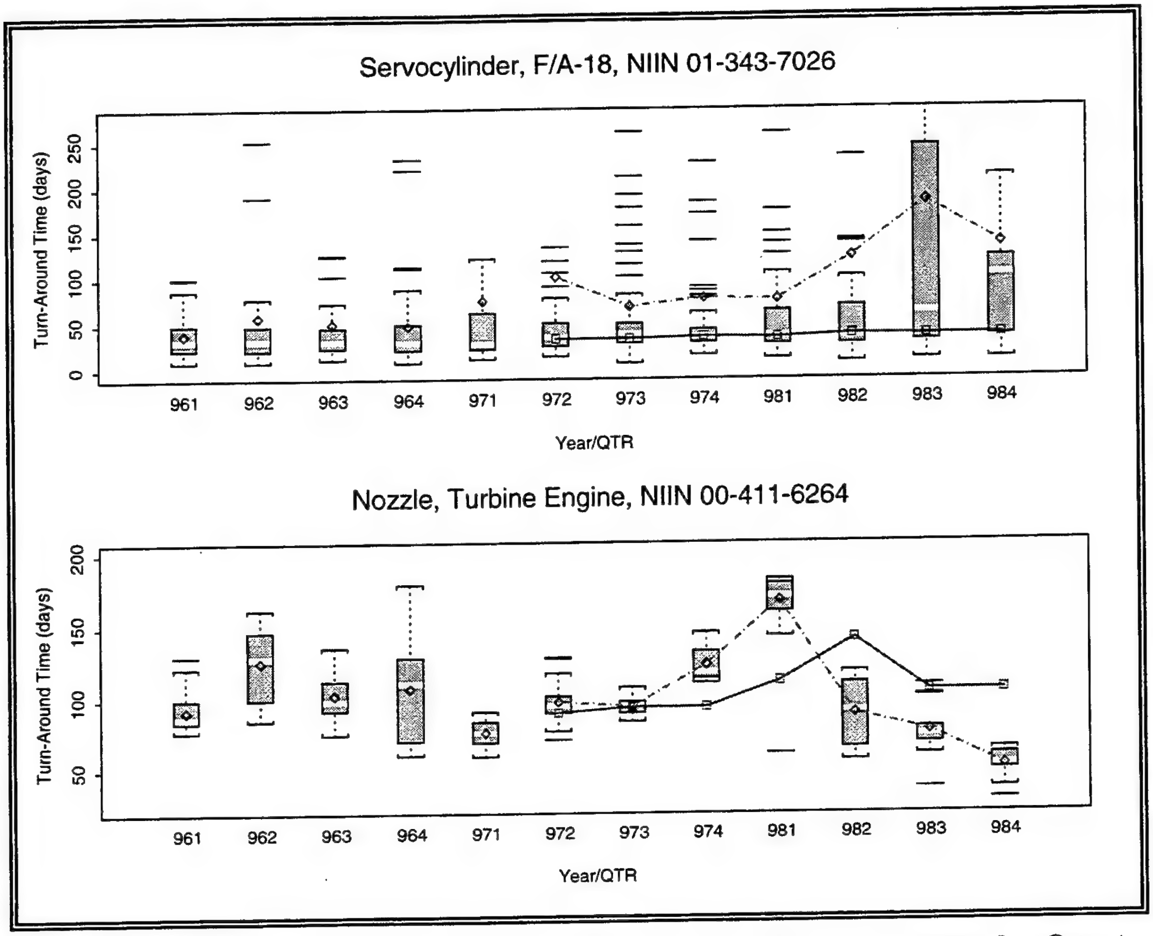

Figure 4.3: Boxplots, Quantity-Weighted Means, and RTAT Forecasts by Quarter for Two Repairable Items. Quarterly RTAT distributions depicted as boxplots are labeled on the x-axis in YYQ format. For example 961 represents 1996, quarter 1. Diamonds represent quantity-weighted average RTAT and are connected by dashed lines. Squares represent forecasts produced by the UICP RTAT forecast model and are connected by solid lines. Some very large observations of RTAT for the Servocylinder, F/A-18 lie beyond the upper boundary of this figure.

3. Comparison of the UICP RTAT Forecast Model to Simple Forecast Methodologies

In this subsection, the UICP RTAT forecast model is compared to three simple forecast methodologies:

- Previous quarter observed value
- Four-quarter moving average
- Exponential smoothing

Forecast accuracy is measured by comparing forecasts produced by these methodologies to actual quarterly quantity-weighted RTAT averages. Mean absolute percentage deviation (MAPD) and mean percentage error (MPE) are used to measure forecast deviation and bias. Because forecasts are produced only for quarters six through twelve in UICP RTAT forecast model analysis, only forecasts produced in those seven quarters by alternative methodologies are used in MAPD and MPE calculations. RTAT values less than four or greater than 998 are excluded as recording errors, in keeping with NAVICP policy.

a. UICP Model Versus Previous-Quarter RTAT Average

Assigning the last-period average value (i.e., the previous-quarter RTAT average) as the forecast for the next period is perhaps the simplest time series analysis forecasting technique. It may be represented mathematically as:

$$\hat{Y}_t = Y_{t-1},$$

where: $\hat{Y}_t$ = forecasted quantity-weighted average RTAT for quarter *t*

Y_{t-1} = actual quantity-weighted average RTAT in quarter *t*-1.

This forecasting methodology works well if there is little variation in observed values from quarter to quarter. It responds fairly well to trends, but does not compensate for cyclic behavior, and it overreacts to random influences (Tersine, 1994). Tables 4.3 and 4.4 give a comparison of UICP model accuracy with previous quarter observed RTAT model accuracy for the 15 items analyzed in this thesis.

The UICP RTAT forecasts have lower MAPD values in eight of 15 items examined. Furthermore, the previous-quarter average produces much larger MAPD

values in three items than even the largest MAPD calculated in the UICP model. MPE values are usually negative under the UICP model, and usually positive under the alternative. It appears that greater bias may exist in the UICP model since RTAT is under-forecast in all seven quarters for four items and a similar degree of consistency is not apparent using the previous-quarter average. Neither technique consistently produces more accurate forecasts than the other.

b. UICP Model Versus Four-Quarter Moving Average RTAT Forecast

The moving average forecast technique generates the next period forecast by averaging a fixed number of previous observations. In this analysis, four is chosen as the number of quarters to be used in the moving average. The formula for the moving average forecast is:

$$\hat{Y}_t = \frac{\sum_{i=1}^{n} Y_{t-i}}{n},$$

where: $\hat{Y}_t$ = forecasted quantity-weighted average RTAT for quarter t

Y_{t-i} = actual quantity-weighted average RTAT for quarter t-i

n = number of time periods included in moving average.

The moving average responds to trends, but lags behind them. If the distribution of quarterly quantity-weighted average RTAT is relatively stationary, the moving average produces forecasts that are fairly constant. The moving average produces less varied forecasts than the "previous-quarter RTAT average" which responds to random variation in the data, but like the latter it does not compensate for cyclic behavior (Tersine, 1994).

Tables 4.3 and 4.4 give a comparison of the forecast accuracy of the UICP model to that of the four-quarter moving average.

Mean absolute percentage deviation and mean percentage error measures shown in Tables 4.3 and 4.4 indicate that the UICP model forecasts appear to have greater bias than the four-quarter moving average forecasts, but neither model produces consistently more accurate RTAT forecasts.

c. *UICP Model Versus Exponential Smoothing Forecast*

Exponential smoothing, also known as exponentially weighted moving averaging, is applied by assigning the most recent quarter observation a weight of *a*, and previous quarter observations progressively decreasing weights, so that all weights sum to 1. Past observations and their weights may be represented by the previous quarter forecast. Exponential smoothing forecasts are calculated using the formula:

$$\hat{Y}_t = aY_{t-1} + (1-a)\hat{Y}_{t-1} \ ,$$

where: $\hat{Y}_t$ = forecast for period t

Y_{t-1} = actual observation in period t-1

a = exponential smoothing weight between 0 and 1.

The exponential smoothing forecast methodology responds to trends, but as with the previously discussed methodologies, it will lag them. It is similar to the moving average in that it smoothes random fluctuations. The responsiveness of exponential smoothing to more recent observations is increased if the smoothing weight a is increased. More sophisticated exponential smoothing methodologies use trend or seasonal components, or both, to account for trends and regular cyclic behavior in data.

The forecast accuracy of simple exponential smoothing with $a = 0.3$ is compared to the accuracy of the UICP model in Tables 4.3 and 4.4.

Results shown in Tables 4.3 and 4.4 indicate that the UICP model forecasts appear to have greater bias than those obtained with exponential smoothing, but neither model produced RTAT forecasts that were significantly more accurate than the other.

d. *Summary of Comparison of UICP Model to Simple Alternative Methodologies*

In this section, UICP RTAT forecast model accuracy is compared to the accuracy of three alternative methodologies, i.e., previous quarter observed RTAT, four quarter moving average, and exponential smoothing. Although the alternative methodologies appear to have produced less-biased forecasts than the UICP model, none of the alternatives is consistently more accurate than the UICP model. Conversely, the UICP model did not forecast more accurately than any of the three simple alternative methodologies.

C. FORECASTING THE NATURAL LOGARITHM OF RTAT

It is apparent from the analyses conducted in previous sections that significant variability exists in quarterly RTAT averages. This variability is partially due to the high influence that observations with large values exert on the quantity-weighted average. It is also apparent from the analyses conducted in Section A of this chapter that the RTAT distributions for many repairable items are positively skewed and exhibit heavy right tails.

One way to avoid large values is to exclude them from calculations. However, excluding only large observations will impart negative bias. As demonstrated in Section

A of this chapter, the UICP RTAT forecast model excluded as outliers only large values of RTAT for most of the items examined. An alternative to excluding outliers is to transform the data so that distributions become more symmetric and exhibit lighter tails. Transforming distributions in this manner will result in the largest and smallest observations having less of an impact on the mean. Although the sample distributions of RTAT for several of the 15 repairable items are even more positively skewed than the lognormal distribution, taking natural logarithms is found to make the distributions more symmetric, while reducing the influence of the largest values on the mean.

Tables 4.3 and 4.4 show the results of applying the deviation and bias measures introduced in this chapter to forecasts of RTAT using the natural logarithm transformation. RTAT forecasts are obtained by using the UICP model to forecast natural logarithm of RTAT from observations of natural logarithm of RTAT and then transforming those forecasts back from logarithmic scale to regular scale. To test the usefulness of the natural logarithm transformation in reducing the effects of outliers, the UICP outlier exclusion criteria are disabled. Mean absolute percentage deviation of forecasts obtained using this method range from 22% to 63% and are listed in Table 4.3. The results are very similar to the results of using the UICP model on the raw data. Accuracy of forecasts produced by the model on raw RTAT data range from 21% to 65%. Mean percentage error (bias) measurements shown in Table 4.4 are also similar for the two models. However, both models produce considerably negatively biased forecasts for most items.

Tables 4.3 and 4.4 also show the results of applying MAPD and MPE measures to UICP model forecasts produced using the natural logarithm transformation, but with the

outlier criteria enabled and the outlier parameter set equal to 1. For many items it is apparent that the outlier exclusion criteria had little impact on forecast accuracy because MAPD and MAD for this model are virtually the same as those for the model that used natural logarithm transformations, but with the outlier criteria disabled.

These results suggest that use of the natural logarithm to transform RTAT data may be beneficial in RTAT forecasting in general, but does not solve the under forecasting problem. Transformation allows the UICP RTAT forecast model to predict RTAT with approximately the same accuracy, but without the use of an exclusion criterion. Appendix D provides graphical justification for transforming RTAT using the natural logarithm function.

D. ASSESSING ADDITIONAL PREDICTABILITY BY ACCOUNTING FOR THE DESIGNATED OVERHAUL POINT

Many of the repairable items managed by NAVICP are repaired by more than one Designated Overhaul Point (DOP). However, the UICP RTAT forecast model does not recognize that the distributions of repair times of an item repaired at different DOPs may be different. An implicit assumption of the UICP RTAT forecast model is that RTAT distributions are the same for a particular repairable item regardless of which of the eligible DOPs performs the overhaul. An analysis of variance (ANOVA) is conducted to examine whether including DOP as a predictor variable for items with multiple DOPs improved the prediction of RTAT. For this exercise two ANOVA models are considered. Model 1 is a one-factor ANOVA that explains the natural logarithm of RTAT using only the repair completion quarter. Model 2 is an additive two-factor ANOVA based on repair completion quarter and DOP. Natural logarithms are used to transform RTAT to make its distributions less skewed. An F-test is conducted to determine whether Model 2

significantly improves the predictive accuracy of Model 1. The proportion of additional variance explained (PVE) by DOP is measured using the formula:

$$\mathrm{PVE} = 1 - \frac{\mathrm{SSE}_2}{\mathrm{SSE}_1} * \frac{df_1}{df_2},$$

where: SSE_2 = sum of squared errors for Model 2 (Model 2 contains DOP as a predictor)

SSE_1 = sum of squared errors for Model 1

df_2 = error degrees of freedom in Model 2

df_1 = error degrees of freedom in Model 1.

Table 4.5 shows the ANOVA results for nine of the 15 repairable items selected for analysis. Each of the nine repairable items is repaired by more than one DOP in at least 4 distinct quarters.

Table 4.5: Analysis of Variance Results Showing Additional Predictability of DOP

NIIN	Number of DOPs	SSE Model 1	DF Model 1	SSE Model 2	DF Model 2	F stat	P value	PVE
00-165-5838	2	405.37	1015	280.8	1014	449.82	0.00	0.31
00-887-1944	3	175.34	437	162.06	435	17.82	0.00	0.07
00-928-0072	2	303.07	898	246.16	897	207.36	0.00	0.19
01-139-7177	2	150.30	255	149.68	254	1.06	0.31	0.00
01-154-2794	5	748.75	513	566.95	509	40.80	0.00	0.24
01-300-0940	5	131.18	283	100.01	279	21.74	0.00	0.23
01-316-3474	3	96.60	410	76.57	408	53.36	0.00	0.20
01-343-7026	2	881.38	891	821.93	890	64.38	0.00	0.07
01-351-3373	3	1002.85	745	941.04	743	24.40	0.00	0.06

Table 4.5 reports ANOVA results for 2 models. In Model 1 RTAT is predicted using only completion quarter, while in Model 2 RTAT is predicted using completion quarter and DOP.

For eight of the nine repairable items analyzed a significant proportion of additional variance is explained by including DOP as a predictor of RTAT, using a 5% test level. A closer look at the data for the only item in which a significant proportion of variance is not explained by including DOP as a predictor of RTAT (NIIN = 01-139-7177, Navigational Unit 1) reveals that only two DOPs are used to repair it. At DOP

N68836, 246 repair observations for this item were completed over all 12 quarters, while at DOP YOK, 21 repair observations were completed over only 5 quarters. The low number of quarters in which both DOPs completed repairs and the low proportion of repairs completed at DOP YOK during those quarters contribute to the lack of statistical significance of DOP in this model.

Of the nine repairable items listed in Table 4.5, the first (NIIN = 00-165-5838, Indicator, Altitude) has the largest proportion of additional variance explained by DOP. Two DOPs repaired this item. At DOP N00244, 918 repair observations were completed over 12 quarters, while at the DOP YOK, 109 repair observations were completed over 11 of the 12 quarters. Figure 4.4 shows the repair times at the two DOPs for this item plotted by quarter.

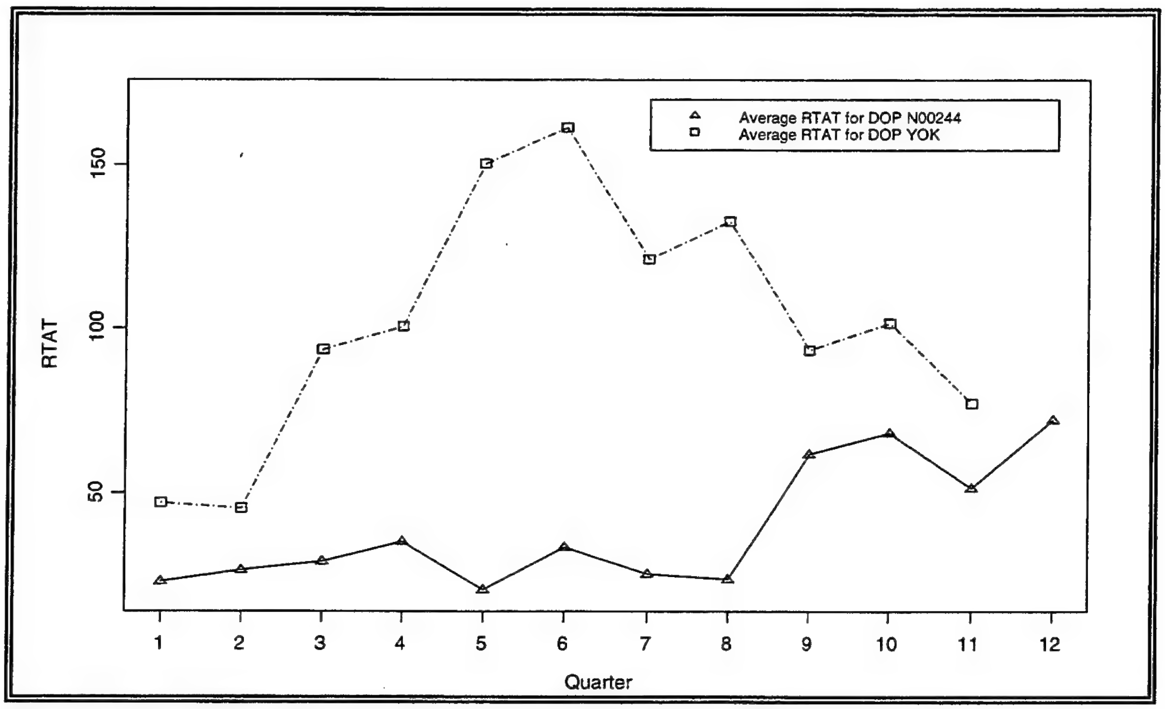

Figure 4.4: Quarterly Average RTAT for Two Different DOPs that Repair Indicator, Altitude, NIIN 00-165-5838. RTAT is measured in days. Quarter is labeled on the horizontal axis. Numbers 1 through 12 refer to the quarter of repair completion. For instance, 1 refers to 1996 quarter 1, while 12 refers to 1998 quarter 4.

Boxplots of both natural logarithm of RTAT and RTAT at each level of completion quarter and DOP for this repairable item are provided in Appendix D. The boxplots support use of the natural logarithm transformation and show that the variances of the various groups of observations appear to be broadly similar (Everitt, 1994).

The analysis of variance conducted in this section indicates that DOP may be a useful predictor of RTAT for multiple-DOP repairable items.

E. AN EVALUATION OF ADDITIONAL PREDICTOR VARIABLES USING REGRESSION ANALYSIS

This section describes regression analyses that are performed to determine the predictive power of regression models containing three additional predictor variables not incorporated by the UICP RTAT forecast model. Table 4.6 describes the additional variables derived for this purpose.

Table 4.11: Additional RTAT Predictor Variables

Data Field	Definition
Pending	Quantity of the item awaiting completion of repair on the last day of the previous quarter
PRatio	*Pending* divided by the sum of *Pending* and quantity of repairs completed in the previous quarter
MedPend	Median time in repair for transactions that were inducted before, but not completed by, the last day of the previous quarter

Each of the additional predictor variables is based on pending repair transactions and is derived from the original database provided by NAVICP-Phil. Repair induction dates are calculated by subtracting RTAT from corresponding completion dates.

Data for repair completions that occur after the fourth quarter of calendar year 1998 are truncated, i.e., not recorded in the NAVICP-Phil database. Consequently, it is not possible to identify with certainty all repairs that are outstanding, especially those that were inducted in later quarters. The analyses described in this subsection deals with truncation by excluding data from 1998, for which truncation is arguably most pronounced. The distributions of repair times for items inducted in calendar year 1996 indicate that few repairs required more than one year to be completed. It therefore appears reasonable to assume that truncation should be a minimal factor in the 1997 data as well.

The variables described in Table 4.6 require information on repairs from the previous quarter. For example, calculation of PRatio requires the number of repairs completed in the previous quarter. Because 1995 data were unavailable, this and other calculations that require lagged information could not be made for the first quarter of 1996. The analysis that follows is therefore based on RTAT completions occurring from the second quarter of 1996 through the fourth quarter of 1997 inclusive.

1. Regression Analysis

In section D of this chapter it was found that including DOP in a model used to predict the natural logarithm of RTAT increases the proportion of variance explained by the model, sometimes substantially. Both to simplify the analysis and to consider repairable items that are not considered in section D, only data for repairable items that are repaired by a single DOP are used in the present analysis.

The analysis proceeds by fitting two linear regression models to the seven quarters of RTAT data. In Model 1 ordinary least squares is used to fit a linear regression

of the natural logarithm of RTAT (dependent variable) on the previous-quarter quantity-weighted average of the natural logarithm of RTAT,

$$\log(Y_{t,i}) = \beta_0 + \beta_1 \log(\overline{Y}_{G,t-1})$$

where: $Y_{t,i}$ = ith observation in quarter t

$\overline{Y}_{G,t-1}$ = Geometric mean of RTAT for quarter $t-1$.

This model attempts to capture essentially the same predictive information used by the UICP RTAT forecast model. In Model 2 the natural logarithm of RTAT (dependent variable) is regressed on Lagged Mean (or previous quarter quantity-weighted average of the natural logarithm of RTAT), *Pending*, *PRatio*, *Medpend* (predictor variables),

$$\log(Y_{t,i}) = \beta_0 + \beta_1 \log(\overline{Y}_{G,t-1}) + \beta_2 Pending + \beta_3 PRatio + \beta_4 \log(MedPend)$$

Model 2 includes the same predictor variable as Model 1 plus three additional predictor variables, which represent information in the NAVICP-Phil data base that is currently not used in making UICP RTAT forecasts. For each item in which the two models are estimated, an *F*-test is conducted to determine if the additional predictor variables make a statistically significant improvement to the prediction of the natural logarithm of RTAT. The proportion of additional variance explained (PVE) by including the three additional predictor variables is calculated for all for which the *F* statistic is significant. The calculation of PVE is the same as that used in section D,

$$PVE = 1 - \frac{SSE_2}{SSE_1} * \frac{df_1}{df_2},$$

where: SSE_2 = sum of squared errors for Model 2 (Model 2 contains three additional predictors)

SSE_1 = sum of squared errors for Model 1

df_2 = degrees of freedom in model 2

df_1 = degrees of freedom in model 1.

Ordinary least squares (OLS) is chosen over quantity weighted least squares (WLS) in order to simplify interpretation of the results. For a reference on regression analysis, see Draper and Smith (1981). Justification for the natural logarithm transformation is provided in Appendix D.

Table 4.7 shows the results of regression analyses conducted on six items that were repaired at only one DOP.

Table 4.7: Regression Analysis of OLS Model with Additional Predictor Variables

NIIN	Sample Size	R^2 Model 1	R^2 Model 2	F	P-value	PVE
01-054-3776	252	0.10	0.14	3.85	0.01	0.03
01-387-0348	180	0.14	0.17	2.01	0.11	0.02
01-011-0855	550	0.05	0.09	8.25	0.00	0.04
01-141-2735	378	0.02	0.19	25.56	0.00	0.16
00-411-6264	120	0.00	0.27	13.98	0.00	0.25
01-062-5846	661	0.00	0.03	6.31	0.00	0.02

Table 4.7 shows significance of Model 2 and proportion of additional variance explained by Model 2 over Model 1. Model 2 includes three additional predictor variables that measure activity at DOP while Model 1 includes only Lagged Mean as a predictor. R^2 is the coefficient of determination and is interpreted as the proportion of variation of RTAT that can be explained by the model.

For five of the six items Model 2 improved significantly (5% test level) on Model 1. The proportion of variance explained by the three additional predictors is considerable for two repairable items (Power Supply LAU-7/A-5, NIIN 01-141-2735 and Nozzle, turbine engine, NIIN 00-411-6264), but fairly low for the others.

Table 4.7 indicates that the additional predictor variables may contribute to the predictability of natural logarithm of RTAT. However, the specific relationships of these variables to repair time are also of interest. An inspection of the *t*-ratios for predictors for each repairable item may indicate which variables are most important. A *t*-ratio is calculated by dividing the estimated regression coefficient by an estimate of its standard error. A *t*-ratio that is large in absolute value suggests that the "true" regression coefficient is different from zero. Table 4.8 provides *t*-ratios and coefficients for the five items in which the models containing additional predictors are found to be significant using the *F*-test.

Table 4.8: Regression Coefficients and *t*-ratios for Items with a Single DOP

NIIN	Sample Size	DOP	Intercept	Lagged Mean	Pending	Pratio	MedPend
01-054-3776	252	LIM	0.31 (0.56)	0.43 (2.32)	0.0078 (1.25)	1.07 (1.08)	**0.31** **(2.27)**
01-011-0855	550	LIW	0.22 (0.12)	1.56 (3.80)	0.0051 (1.06)	**-4.80** **(-3.01)**	-0.08 (-0.53)
01-141-2735	378	N68836	5.92 (2.31)	-0.80 (-1.33)	**0.0082** **(1.77)**	-3.33 (-1.12)	0.06 (0.41)
00-411-6264	120	N00146	2.98 (3.57)	-0.08 (-0.47)	**-0.0004** **(-1.66)**	**1.67** **(5.81)**	**0.28** **(5.10)**
01-062-5846	661	N00146	3.77 (3.35)	0.28 (1.50)	**0.0137** **(2.62)**	-2.19 (-1.63)	**-0.42** **(-2.26)**

Table 4.8 shows both regression coefficients (β) and *t*-ratios for Model 2. Bold is used for regression coefficients that are statistically significant at level α=0.10

The *t*-ratios in Table 4.8 indicate that none of the three additional predictor variables is significant in all of the five models at the $\alpha = 0.05$ level (absolute value of 1.96 or greater), but at least one of them is significant at the $\alpha = 0.10$ level (absolute value of 1.645 or greater) in each model. Corresponding values for the significant coefficients ($\alpha = 0.10$) do not appear to demonstrate any distinct patterns.

It is plausible that although relationships exist between these variables and RTAT that the relationships differ between individual items due to differences in the ways that dissimilar items are repaired. It is possible that consistent relationships between these variables and RTAT exist in repairable items that belong to the same DOP. To examine this hypothesis a regression analysis is conducted with data for eight different items that were repaired at the same designated overhaul point N68836. Only one of these items (Power Supply, LAU-7/A-5, NIIN 01-141-2735) is a member of the fifteen-item subset chosen for analysis. As mentioned in Chapter III, the other seven items are included only in the analyses conducted here. They are those items that have the highest extended standard prices of all items repaired exclusively at DOP N68836. Extended standard price is the product of the per-unit price of the item and the total quantity of the item repaired. Table 4.9 summarizes the results of the regression analysis.

Table 4.9: Regression Analysis for Items Repaired by DOP N68836

NIIN	Sample Size	R2 Model 1	R2 Model 2	*F*	P-value	PVE
01-223-5107	184	0.00	0.29	24.29	0.00	0.28
01-142-8815	168	0.00	0.21	14.29	0.00	0.19
01-141-2735	378	0.02	0.19	25.56	0.00	0.16
01-120-4885	290	0.01	0.18	20.64	0.00	0.17
01-131-4730	148	0.00	0.45	39.03	0.00	0.44
99-257-1090	98	0.01	0.10	2.89	0.04	0.06
00-020-3211	148	0.06	0.18	7.15	0.00	0.11
01-018-7764	112	0.01	0.08	2.40	0.07	0.04

In seven of the eight items depicted in Table 4.9, Model 2 produced an improvement over Model 1 at the $\alpha = 0.05$ test level. The proportion of variance explained by the three additional predictor variables is considerable for several of the

repairable items, indicating that useful predictive relationships between RTAT and some of the variables may exist. An examination of model coefficients may indicate patterns among the repairable items overhauled by DOP N68836.

Table 4.10 provides *t*-ratios and coefficients for all items considered in Table 4.9. High significance of coefficients for the three additional predictor variables ($\alpha = 0.10$) indicate that for many of the items repaired by DOP N68836 the additional predictor variables may be useful in predicting RTAT. However, examination of the coefficients for those variables does not suggest any obvious patterns relating RTAT and the predictor variables for items repaired at DOP N68836. The regression models and model diagnostics for the Power Supply, LAU-7/A-5 are provided in Appendix E.

Table 4.10: Regression Coefficients and *t*-ratios for Items with DOP N68836

NIIN	Sample Size	Intercept	Lagged Mean	Pending	Pending Ratio	Log of Medpend
01-223-5107	184	**2.16** **(2.93)**	0.04 (0.12)	0.01 (1.01)	0.83 (0.59)	0.24 (1.08)
01-142-8815	168	**4.42** **(6.48)**	-0.30 (-1.48)	**-0.02** **(-2.15)**	**4.48** **(4.87)**	**-0.17** **(-2.29)**
01-141-2735	378	**5.68** **(7.02)**	**-0.74** **(3.10)**	**0.01** **(3.95)**	**-3.06** **(-2.36)**	0.08 (1.22)
01-120-4885	290	**1.80** **(2.58)**	0.24 (1.15)	**0.03** **(7.24)**	**-2.28** **(-3.68)**	**0.20** **(4.13)**
01-131-4730	148	0.91 (1.29)	**0.41** **(3.28)**	**0.02** **(7.62)**	**0.99** **(1.71)**	0.06 (1.08)
99-257-1090	98	**2.59** **(3.61)**	**0.41** **(1.83)**	**0.05** **(1.91)**	**-1.54** **(-1.92)**	-0.13 (-1.31)
00-020-3211	148	**5.07** **(4.63)**	**-0.76** **(-2.14)**	**-0.02** **(-3.00)**	**4.05** **(3.79)**	**0.19** **(2.26)**
01-018-7764	112	**2.58** **(2.63)**	0.39 (1.54)	**-0.01** **(-1.80)**	0.67 (1.10)	-0.04 (-1.07)

Bold is used for regression coefficients that are statistically significant at level α=0.10

2. Summary of Regression Analysis

Regression analysis detected additional predictability of repair times in the NAVICP-Phil data by using measures that are not incorporated in the UICP RTAT forecast model. In some cases, considerable additional variance may be explained by the variables. However, examination of coefficients for the additional predictors suggests no clear relationships between them and RTAT across various repairable items. These findings suggest that it may be difficult to make a simple modification to the UICP forecasting tool to exploit the predictive improvement that would be gained by including the additional variables in its algorithms. Nonetheless, these results point to additional information contained in the queueing aspect of the repair process.

V. SUMMARY AND CONCLUSIONS

To efficiently manage its stocks of repairable items, NAVICP must be able to forecast repair times of the items that it sends to overhaul points for repair. Because repair turn-around time (RTAT) for several thousand items must be forecast on a quarterly basis, NAVICP developed an automated forecasting tool, known as the UICP RTAT forecast model, that uses a common methodology for each item. The research described in this thesis considers the accuracy of the UICP RTAT forecast model from several different perspectives:

1) The accuracy of prediction of the UICP RTAT forecast model across a subset of repairable items chosen to represent high-value, high-volume repair activities;

2) The accuracy of alternative forecasting methodologies, including exponential smoothing, four-quarter moving averaging, and use of the previous quarter average RTAT value;

3) The validity of assumptions implicit in the UICP RTAT forecast model and the impact that these assumptions have on forecast accuracy;

4) The ability of additional predictor variables from the same data used in current RTAT forecasting to improve the prediction of repair times.

None of the simple alternative methodologies that are considered in this thesis are found to perform significantly better than the UICP RTAT forecast model. Conversely, forecasts produced by the UICP model are not consistently more accurate than forecasts produced by any of the alternative methodologies.

UICP RTAT model forecasts are found to exhibit substantial negative bias. One source of this bias is the outlier screening used in the UICP RTAT model, which tends to exclude many more large RTAT values than small ones, due to the highly positively skewed distributions of repair times encountered. It is found that a simple,

but effective remedy for the problem of excluding disproportionate numbers of large RTAT observations is to apply a logarithm transformation to the RTAT values before UICP processing. Although many of the distributions of RTAT for the items examined are more highly skewed than the lognormal distribution, natural logarithm transformations produce nearly symmetric RTAT distributions for most items, and reduce the impact of outliers in all cases. Accuracy of the UICP RTAT forecast model on data transformed using the natural logarithm is about the same as model accuracy on raw RTAT data, but the transformation does not solve the problem of underforecasting. The benefit of using the logarithmic transformation is that it may reduce or eliminate the need for outlier exclusion. Consequently the amount of information discarded may be reduced.

For items that are sent to more than one designated overhaul point (DOP) for repair, it is found that accounting for the DOP may significantly improve the prediction of repair turn-around times. Some DOPs are found to take longer to repair a given item than others.

Because the UICP model forecasts RTAT based solely on repair transactions that have been completed, it ignores the present state of the repair process and the queueing aspect of this process. In conducting the thesis research, additional variables are derived from the NAVICP-Phil database to capture these aspects. It is found that significant improvement in the prediction of RTAT may be realized by considering the additional variables in a forecasting model. However, no clear or simple means are found by which the existing model could be modified in order to realize these gains. Adopting a regression approach in the forecasting model may be more difficult than incorporating the

DOP factor, but in both cases results point to the use of queueing information to obtain more accurate RTAT forecasts.

This thesis makes two recommendations to improve the forecast accuracy of Navy repair turn-around times:

1. Incorporate DOP as a predictor of RTAT for items repaired by more than one DOP in future model development.

2. Identify and collect data on variables that capture the queueing aspect of the repair process. Incorporate the queueing aspect of the repair process in future forecast model development.

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APPENDIX A: S-PLUS FUNCTIONS USED TO CODE UICP RTAT FORECAST MODEL

The S-Plus functions that follow were used to produce a single forecast of RTAT from any number of quarters of RTAT observation data. The first function listed, **forecast.tat**, is the "main" forecast function. Arguments to **forecast.tat** consist of:

- *dfr*: an S-plus data frame of observations of the form described in Chapter III
- *file*: the RTAT forecast from the previous quarter
- *ftm*: a numeric vector of quantity weighted averages of RTAT; will be NULL unless RTAT is determined to be stable the previous quarter
- *fence*: the numeric year and quarter (YYQ) of the oldest quarter in last trend window if a trend was detected by the model in a previous forecast quarter, or the year and quarter of the oldest quarter in the most recent half of the data if a process change was detected by the model in a previous forecast quarter

The remaining functions are called either by **forecast.tat** or by other functions called by **forecast.tat**. Several function names correspond to flowchart blocks shown in the UICP RTAT Forecast Model Flowchart (Figure 2.1).

```
#Function name : forecast.tat
function(dfr, file, ftm, fence)
{
########################################################################
# This function forecasts RTAT by selecting a methodolgy based on trend
# detection, process change detection, and the results of 4 Statistical
# Process Tests.  The function returns a five element List.  The first
# element contains the numeric forecast, the second element contains a
# string indicating which of the forecast methodologies was used.  The
# third contains the new forecast tracking mean (FTM) if none of the
# SPC tests failed, or NULL vector if a new forecast was generated
# because of process change or trend detection.  The fourth contains a
# logical vector indicating which of the four SPC tests failed or NULL
# if none did.  The fifth contains the fence (YYQ).
#   dfr:   a data frame of RTAT observations containing thirteen
#          columns
#   file:  file RTAT
#   ftm:   the forecast tracking mean vector (may be a zero length
#          numeric vector)
#   fence: the fence in YYQ - no data occurring before the fence is
#          considered
########################################################################
```

```
dfr <- c1a(dfr)    #consolidate batches, identify recording errors
      dfr <- c1b(dfr, 1)          #outlier criteria on
      #identify outliers, fourth spread multiplier parameter set to 1
      qtr.avg <- c2(dfr)          #calculate quarterly quantity weighted
                                   averages
      qtr.avg <- qtr.avg[(qtr.avg[, 1] >= fence),  ]
      # if there are less than five quarters of data as recent or more
      # recent than the fence calculate and return the quantity
      # weighted average.
      if(length(qtr.avg[, 1]) < 5) {
            qty.wt.avg <- c8(dfr, fence)
            return(qty.wt.avg, "A Quantity weighted average of all of
data", vector(mode = "numeric", length = 0), NULL, fence)
      }
      process.change <- d5(qtr.avg, 0.5)  #process change detection
      # if a process change is detected, then return the quantity
      # weighted average of the most recent half of the data
      if(process.change[1]) {
            qty.wt.avg <- c9(dfr, process.change[2])
            return(qty.wt.avg,
                  "H Quantity weighted average of most recent half of
data", vector(ode = "numeric", length = 0), NULL, process.change[2])
      }
      else {
            trend <- c3(qtr.avg)
            # if a trend is detected and the Sen median regression
            # forecast is greater than or less than all of the
            # quarterly averages, return the iterative expontial
            # smoothing forecast
            # else return the Sen median regression forecast.
            if(trend[1]) {
                  #compute a vector of qtrly avges at least as recent
                  # as the fence
                  wtv <- qtr.avg[, 1] >= trend[2]
                        SEN.forecast <- c10(qtr.avg[wtv, 2])
                  if(SEN.forecast[2]) {
                        iter.exp <- c11(qtr.avg[wtv, 2], 0.4)
                        return(iter.exp, "E iterative exponential
smoothing", vector(mode = "numeric", length = 0), NULL, trend[2])
                  }
                  else {
                        return(SEN.forecast[1], "M SEN median
                        regression", vector(mode = "numeric", length =
                        0), NULL, trend[2])
                  }
            }
            else {
                  qty.wt.all <- c4(dfr, fence)
                  ftm <- c(ftm, qty.wt.all)
                  SPC <- c12(ftm, file, fence)
                  # if none of the SPC tests fail, return the file
                  # RTAT, and the new ftm vector, else return the
                  # quantity weighted average of all observations.
                  if(SPC[[1]] == "stable") {
                        return(file, "S stable item", ftm, NULL, fence)
                  }
```

```
                else {
                      return(SPC)
                }
          }
    }
}


#Function name: c1a
function(X)
{
########################################################################
# c1a
#  This is the consolidate batch function.  It also enters "Z" in the
#  exclusion indicator field (column 12) of every TAT observation less
# than 4 or greater than 998.  All observations with the same TAT, comp
# date, and DOP are consolidated into a single observation with the
# quantity field adjusted accordingly.  A data frame of consolidated
# observations is returned.
#     X: a data frame of repair observations for a single NIIN
########################################################################
#
      n <- dim(X)[1]
      xp <- paste(X[, 7], X[, 8], X[, 9], sep = "")
      ix <- order(xp)   # Puts columns 7-9 in sorted order.
      ixj <- ix[1]
      xkeep <- rep(T, n)      # Note deletions while looping
      for(j in 2:n) {
            if(xp[ix[j]] == xp[ixj]) {
                  xkeep[ix[j]] <- F
                  X[ixj, 6] <- X[ixj, 6] + X[ix[j], 6]
            }
            else {
                  ixj <- ix[j]
            }
      }
      X <- X[xkeep,  ]
      X <- out1(X, 4, 998) # Enter "Z" in the exclusion field of
recording errors
      return(X)
}
```

```
#Function name: out1
function(dframe, lower, upper)
{
########################################################################
#   out1
# This function identifies those values of RTAT considered errors by
# changing the exclusion indicator (column 12) to "Z".  Returns the
# data frame with the modified exclusion indicator column.
#
#   dframe: a data frame with col 7 containing values of RTAT
#   lower:  the lowest acceptable value of RTAT (usually 4)
#   upper:  the highest acceptable value of RTAT (usually 998)
########################################################################
#
# first make the factor data in col 12 (excl indicator) character data
      dframe[, 12] <- I(as.character(dframe[, 12]))
      temp <- as.numeric(dframe[, 7])
      for(k in 1:length(temp)) {
            if((temp[k] < lower) | (temp[k] > upper) |
(is.na(temp[k]))) {
                  dframe[k, 12] <- "Z"
            }
      }
      return(dframe)
}


#Function name: c1b
function(dfr, p)
{
########################################################################
# c1b
# This function excludes EDA outliers.  The data frame of RTAT
# observations is returned with the exclusion indicator fields of
# excluded observations appropriately modified.
#
#    dfr: a data frame of RTAT observations which should already have
#         been consolidated (c1a)
#    p:   the outlier parameter which multiplies fourth spread
#
# If any observations lie outside of the boundaries determined by
# adding fourth spread to the upper fourth and subtracting fourth
# spread from the lower fourth, they are considered outliers.
# Observations identified as outliers will have their exclusion
# indicator (col 12) set to Q or P.
########################################################################
#
# create a vector of RTAT.  Remove all observations that have "Z" in
# exclusion indicator field,then sort the vector by RTAT in ascending
# order.
      rtat <- dfr[, 7]
      for(k in 1:length(rtat)) {
            if(dfr[k, 12] == "Z") {
                  rtat[k] <- NA
            }
      }
```

```
      rtat <- sort(rtat, partial = NULL, na.last = NA)
      # determine fourth spread and the outlier boundaries (IFL, IFU).
      long <- length(rtat)
      fl <- long * 0.25
      FL <- ((rtat[ceiling(fl)] - rtat[floor(fl)]) * (fl - floor(fl)))
+ rtat[floor(fl)]
      fu <- long * 0.75
      FU <- ((rtat[ceiling(fu)] - rtat[floor(fu)]) * (fu - floor(fu)))
+ rtat[floor(fu)]
      FS <- FU - FL
      IFL <- FL - (p * FS)
      IFU <- FU + (p * FS)
      # if any TAT observation lies outside of the boundaries, set the
      # exclusion indicator to Q or P.  First, convert the factor
      # variable dfr[,12] to character.
      dfr[, 12] <- I(as.character(dfr[, 12]))
      for(j in 1:length(dfr[, 12])) {
            if(((dfr[j, 7] < IFL) || (dfr[j, 7] > IFU)) && (dfr[j, 12]
!= "L") &&
                  (dfr[j, 12] != "Z")) {
                   dfr[j, 12] <- "P"
            }
            else if(((dfr[j, 7] < IFL) || (dfr[j, 7] > IFU)) && (dfr[j,
12] == "L") &&
                  (dfr[j, 12] != "Z")) {
                   dfr[j, 12] <- "Q"
            }
      }
      return(dfr)
}


#Function name: c2
function(dfr)
{
########################################################################
# c2
# This function calculates weighted quarterly average RTAT and returns
# a matrix with YYQ in the first column and quarterly average RTAT in
# the second.
#
#    dfr: a data frame of RTAT observations which should already have
#         been consolidated (c1a), and sent through the exclusion
#         function (c1b)
#
# If any observations are exclusions, they will be removed.  Exclusions
# are identified as those observations containing "Q", "P", "Z", or "L"
# in the exclusion field.
########################################################################
#
# Calculate quantity weighted mean by quarter.
# Do not consider excluded observations.
      tnm <- !is.na(dfr[, 7]) & !is.na(dfr[, 6]) & (dfr[, 12] != "Q") &
(dfr[, 12] !=
            "P") & (dfr[, 12] != "Z") & (dfr[, 12] != "L")
```

```
      yrqtr <- makeyrqtr(dfr[, 8])
      X <- statby(dfr[, 7][tnm] * dfr[, 6][tnm], yrqtr[tnm], "sum")
      Y <- statby(dfr[, 6][tnm], yrqtr[tnm], "sum")
      wtmean <- X[, 3]/Y[, 3]
      YYQ <- X[, 1]
      return(cbind(YYQ, wtmean))
}


#Function name: makeyrqtr
function(x)
{
##########################################################################
# This function turns julian date into yrqtr (YYQ): 96021 ==> 961,
# 98100 ==> 982, 00300 ==> 004, etc.  A numeric element or vector with
# numeric elements YYQ is returned.
#      X: A data frame or RTAT observations
##########################################################################
      yr <- floor(0.001 * x)
      n <- length(x)
      qtr <- numeric(n)
      nodays <- x - 1000 * yr # Returns number of days into year
      qtr[yr == 96 & nodays < 92] <- 1
      qtr[yr == 96 & nodays >= 92 & nodays < 183] <- 2
      qtr[yr == 96 & nodays >= 183 & nodays < 275] <- 3
      qtr[yr == 96 & nodays >= 275] <- 4
      qtr[yr != 96 & nodays < 91] <- 1
      qtr[yr != 96 & nodays >= 91 & nodays < 182] <- 2
      qtr[yr != 96 & nodays >= 182 & nodays < 274] <- 3
      qtr[yr != 96 & nodays >= 274] <- 4
      return(yr * 10 + qtr)
}


#Function name: c3
function(m)
{
###########################################################################
# c3
# This function performs  Kendall Trend Detection.  A three-element
# vector is returned.
#The first element is boolean, True if trend detected, False if not.
# The second is the new fence (YYQ) if a trend was detected, if not the
# second is the oldest quarter contained in the data frame (m) as YYQ.
# The third is W, the trend window, if a trend was detected; the length
# of the columns in the matrix m if not.
#
#     m: a 2 column matrix.  The first column is year and quarter
#        YYQ) sorted  from oldest to most recent.  The second column
#        contains the corresponding quarterly quantity weighted average
#         RTAT.
###########################################################################
      #re-sort m to go from newest to oldest quarterly qty-weighted
      #average RTAT.
```

```
        m <- m[rev(order(m[, 1])),  ]
        W <- 4
        QTR <- length(m[, 1])
        done <- F
        while((!done) & (W < 10) & (W < QTR)) {
                W <- W + 1
                if(W == 5) {
                        TP <- 6
                }
                else if(W == 6) {
                        TP <- 9
                }
                else if(W == 7) {
                        TP <- 10
                }
                else if(W == 8) {
                        TP <- 13
                }
                else if(W == 9) {
                        TP <- 15
                }
                else if(W == 10) {
                        TP <- 18
                }
                S <- 0
                for(i in 1:(W - 1)) {
                        for(j in (i + 1):W) {
                                if(m[i, 2] > m[j, 2]) {
                                  S <- S + 1
                                }
                                else if(m[i, 2] < m[j, 2]) {
                                  S <- S - 1
                                }
                        }
                }
                if((S >= TP) || (S <= (-1 * TP))) {
                        done <- T
                        return(as.vector(c(done, m[W, 1], W)))
                }
        }
        return(as.vector(c(done, m[QTR, 1], QTR)))
}


#Function name: c4
function(d, f)
{
######################################################################
# c4
# This function calculates and returns quantity weighted mean of
# observations occurring on or after the fence (f).  Used when neither
# a trend nor a process change is detected.  Note: functions c4, c8,
# and c9 are identical.
#
#    d: a data frame of RTAT observations.
#    f: the fence in YYQ
############################
```

```
      yrqtr <- makeyrqtr(d[, 8])
      tnm <- (!is.na(d[, 7])) & (!is.na(d[, 6])) & (yrqtr >= f) & (d[,
12] != "Z") & (d[
            , 12] != "Q") & (d[, 12] != "P") & (d[, 12] != "L")
      X <- sum(d[, 7][tnm] * d[, 6][tnm])
      Y <- sum(d[, 6][tnm])
      wtmean <- X/Y
      return(wtmean)
}


#Function name: c8
function(d, f)
{
########################################################################
# c8
# This function calculates and returns quantity weighted mean of
# observations occurring on or after the fence (f).  Function is used
# when there are fewer than five quarters of observations occurring
# during or after the fence.
#
#    d: a data frame of RTAT observations.
#    f: the fence in YYQ
########################################################################
      yrqtr <- makeyrqtr(d[, 8])
      tnm <- (!is.na(d[, 7])) & (!is.na(d[, 6])) & (yrqtr >= f) & (d[,
12] != "Z") & (d[
            , 12] != "Q") & (d[, 12] != "P") & (d[, 12] != "L")
      X <- sum(d[, 7][tnm] * d[, 6][tnm])
      Y <- sum(d[, 6][tnm])
      wtmean <- X/Y
      return(wtmean)
}


#Function name: c9
function(d, f)
{
########################################################################
# c9
# This function calculates and returns quantity weighted mean of the
# data occurring during and after the fence (f) detected by process
# change detection (d5).
#
#    d: data frame of RTAT observations for one NIIN
#    f: fence in YYQ
########################################################################
# calculate quantity weighted mean of all non excluded observations
# occurring on or after the YYQ indicated by the fence (f)
      yrqtr <- makeyrqtr(d[, 8])
      tnm <- (!is.na(d[, 7])) & (!is.na(d[, 6])) & (yrqtr >= f) & (d[,
12] != "Z") & (d[, 12] != "Q") & (d[, 12] != "P") & (d[, 12] != "L")
      X <- sum(d[, 7][tnm] * d[, 6][tnm])
      Y <- sum(d[, 6][tnm])
      wtmean <- X/Y
      return(wtmean)
}
```

```
#Function name: c10
function(v)
{
########################################################################
# This function performs Sen median regression as defined by the RTAT
# forecast model.
# A vector is returned.  The first element contains the SEN median
# regression forecast of RTAT.  The second element contains a boolean
# set to T if the forecast is either greater than the largest average
# RTAT value contained in vector v or less than the smallest.
# (D10 and D11 decisions are therefore contained in this function)
#
#  v: a sorted vector of the W most recent quarterly quantity weighted
#     avg  RTATs, where the oldest observation is in vector index 1,
#     and the most recent is in vector index W.
########################################################################
# Compute the slopes (M) of the lines connecting all quarterly averages
# to all other quarterly averages.
      M <- vector(mode = "numeric", length = 0)
      W <- length(v)
      for(i in 1:(W - 1)) {
            for(j in (i + 1):W) {
                  M <- c(M, ((v[j] - v[i])/(j - i)))
            }
      }
# Find the median slope (B), the median RTAT (R), and the median RTAT
# observation number (X).  Then compute and return the RTAT forecast
# and the boolean indicating a lower or upper bounds violation.
      B <- median(M)
      R <- median(v)
      if(W/2 == floor(W/2)) {
            X <- W/2 + 0.5
      }
      else {
            X <- ceiling(W/2)
      }
      a <- R - (B * X)
      RTAT <- a + (B * W)
      if((RTAT > max(v)) || (RTAT < min(v))) {
            return(as.vector(c(RTAT, T)))
      }
      else {
            return(as.vector(c(RTAT, F)))
      }
}
```

```
#Function name: c11
function(v, a)
{
###########################################################################
# c11
# This function performs iterative exponential smoothing of the last W
# RTAT quarterly averages.  The iterative exponentially smoothed RTAT
# forecast is returned.  Note: the forecast is .5 rounded (.5 is
# rounded to the even digit).
#
#   v: a vector of the W most recent quarterly quantity weighted
#      average RTATs, where the oldest observation is in vector index
#      1, and the most recent is in vector index W.
#   a: the exponential smoothing weight parameter
###########################################################################
# Compute the interim forecasts and the final forecast.  Store those
# values in a vector
# (Fore).
      Fore <- vector(mode = "numeric", length = 0)
      Fore <- c(Fore, a * v[2] + (1 - a) * v[1])
      W <- length(v)
      for(i in 3:W) {
            Fore <- c(Fore, a * v[i] + (1 - a) * Fore[i - 2])
      }
      return(round(Fore[length(Fore)], 0))
}


#Function name: c12
function(ftm, file, fence)
{
###########################################################################
# c12
# This function calls the 4 SPC test functions.
# If any of the SPC tests returns T, a list is returned.  The first
# element contains the new forecast (qty weighted average of all
# observations).  The second element is a string describing which of
# the four tests failed first.  The third element contains an empty
# vector (the new ftm).  The fourth is a logical four element vector
# indicating which of the SPC tests failed (T), and which did not (F).
# The fifth is the fence passed to the function.
# If all SPC tests return F, "stable" is returned.
#
#    ftm:    a vector of length SPCQTR of qty weighted mean RTAT of all
#            observations corresponding to the SPC qtr.
#    file:   the file RTAT
#    fence: the fence(YYQ)
###########################################################################
# all of the explicit values contained in the test.failures assignment
# are parameters described in the respective SPC functions (bias, runs,
# cumbias, conf)
####
      ftm <- as.numeric(ftm)
      test.failures <- c(bias(ftm[length(ftm)], file, -0.15, 0.15),
runs(ftm, file, 0.05, 0.05, -3, 3), cumbias(ftm, file, -0.1, 0.1),
conf(ftm, file, 0.9))
```

```
	if(test.failures[1] == T) {
		return(ftm[length(ftm)], "B Failed Bias Test", vector(mode
= "numeric", length = 0), test.failures, fence)
	}
	else if(test.failures[2] == T) {
		return(ftm[length(ftm)], "R Failed Runs Test", vector(mode
= "numeric", length = 0), test.failures, fence)
	}
	else if(test.failures[3] == T) {
		return(ftm[length(ftm)], "B Failed Cumulative Bias Test",
vector(mode = "numeric", length = 0), test.failures, fence)
	}
	else if(test.failures[4] == T) {
		return(ftm[length(ftm)], "I Failed Confidence Interval
Test", vector(mode = "numeric", length = 0), test.failures, fence)
	}
	else if(sum(test.failures) == 0) {
		return("stable")
	}
}
```

```
Function name: bias
function(ftm, file, lower, upper)
{
#######################################################################
# bias
# This is SPC test 1, the Bias Test
#    ftm: the current quarter Quantity Weighted Average of RTAT
#    file: the File RTAT
#    lower: the lower bias parameter
#    upper: the upper bias parameter
# If bias is outside of the bias parameters, true is returned.  This
# indicates a test failure, and is reason to consider updating the File
# RTAT.
#######################################################################
	b <- (ftm - file)/file
	if((b <= lower) | (b >= upper)) {
		return(T)
	}
	else {
		return(F)
	}
}
```

```
#Function name: cumbias
function(ftm, file, lower, upper)
{
########################################################################
# cumbias
# This is SPC test 3, the Cumulative Bias Test
#   ftm:  a vector of qty weighted mean RTAT of all observations
#         calculated at the corresponding SPC quarter
#   file: the current file RTAT
#   lower: the lower cum average bias parameter
#   upper: the upper cum average bias parameter
# A test failure occurs when the cumulative bias is outside of the
# lower and upper bias parameters.  True is then returned, indicating
# that file RTAT should be considered for update with current FTM.
# Note: Must have at least 3 SPC quarters to run this test.
########################################################################
      if(length(ftm) < 3) {
            return(F)
      }
      cum <- 0
      bias <- (ftm - file)/file
      for(k in 1:length(ftm)) {
            cum <- cum + bias[k]
            if((cum >= upper) | (cum <= lower)) {
                  return(T)
            }
      }
      return(F)
}


#Function name: runs
function(ftm, file, lowerRuns, upperRuns, lowerMC, upperMC)
{
########################################################################
# runs
# This is SPC test 2, the Runs Test
#   ftm:    a vector of qty weighted mean RTAT of all observations
#           calculated at the corresponding SPC quarter
#   file:   the current file RTAT
#   lowerRuns: the lower Runs Parameter
#   upperRuns: the upper Runs Parameter
#   lowerMC:   the lower mean counter parameter
#   upperMC:   the upper mean counter parameter
# This test fails when the mean counter is less than the lower or
# greater than the upper mean counter parameters.  True is returned
# upon test failure, indicating that File RTAT should be considered for
# update with FTM.
########################################################################
#
      nftm <- length(ftm)
      filemc <- 0
      bias <- (ftm - file)/file
      for(k in 1:nftm) {
            if((bias[k] > lowerRuns) & (bias[k] < upperRuns) & (filemc
            > 0) &
```

```
                  (bias[k] < 0)) {
                   filemc <- 0
            }
            else if((bias[k] > lowerRuns) & (bias[k] < upperRuns) &
(filemc < 0) &
                  (bias[k] > 0)) {
                   filemc <- 0
            }
            else if((bias[k] >= upperRuns) & (filemc <= 0)) {
                   filemc <- 1
            }
            else if((bias[k] < lowerRuns) & (filemc >= 0)) {
                   filemc <- -1
            }
            else if((bias[k] >= upperRuns) & (filemc >= 0)) {
                   filemc <- filemc + 1
            }
            else if((bias[k] <= lowerRuns) & (filemc <= 0)) {
                   filemc <- filemc - 1
            }
            if((filemc >= upperMC) | (filemc <= lowerMC)) {
                   return(T)
            }
      }
      return(F)
}


Function name: conf
function(ftm, file, int)
{
########################################################################
# conf
# This is SPC test 4, the Confidence Interval Test
#   ftm:  a vector of qty weighted mean RTAT of all observations
#         calculated at the corresponding SPC quarter
#   file: the current file RTAT
#   int:  the confidence interval width (either .9 or .95)
# This test fails when the File RTAT is outside of the confidence
# interval computed for the data.  True is returned, indicating that
# file RTAT should be considered for update.
# Note: Must have at least 3 SPC quarters to run this test.
########################################################################
      if(length(ftm) < 3) {
            return(F)
      }
      z <- t.test(ftm, y = NULL, alternative = "two.sided", mu = file,
paired = F,
            var.equal = T, conf.level = int)
      if((file > z[[4]][2]) | (file < z[[4]][1])) {
            return(T)
      }
      else {
            return(F)
      }
}
```

```
#Function name: d5
function(dfr, p)
{
##########################################################################
# d5
# This function detects a process change (d5).  A three element vector
# is returned if a process change is detected.  The first element is a
# booelan set to True.  The second element is numeric YYQ that is set
# to YYQ of the most recent half of the data.  The third element is the
# number of quarters in the most recent half of the data.  If
# a process change is not detected F, NULL, NULL is returned.
#
#     dfr: a matrix of RTAT containing YYQ in the first column, and
#          quantity weighted average RTAT in the second.  It contains
#          only those qtrly average RTAT values as recent or more recent
#          than the fence.
#     p:   a parameter limiting the allowed absolute value of the
#          difference between the values obtained from the two halves of
#          the data (eg 0.5).
##########################################################################
#Divide the data into the most recent half of the quarters and the
#oldest half of the quarters.  Use only the last 10 quarters of data.
      long <- length(dfr[, 1])
      if(long > 10) {
            dfr <- remove.row(dfr, 1, long - 10)
            dfr
            long <- length(dfr[, 1])
      }
      recent <- ceiling(long/2)
      old <- long - recent
      #find the average RTAT of the most recent and oldest half of data
      sum <- 0
      for(j in 1:old) {
            sum <- sum + dfr[j, 2]
      }
      A1 <- sum/old
      sum <- 0
      for(k in (old + 1):long) {
            sum <- sum + dfr[k, 2]
      }
      A2 <- sum/recent
      # calculate the difference between the averages of the quarterly
      # averages
      diff <- (A2 - A1)/max(A2, A1)
      # if the difference falls outside of the parameters, return T,
      # otherwise return F
      if((diff > p) || (diff < (-1 * p))) {
            return(as.vector(c(T, dfr[old + 1, 1], recent)))
      }
      else {
            return(as.vector(c(F, NULL, NULL)))
      }
}
```

APPENDIX B: NAVICP-PHIL DATA SET (1996-1998)

Table B.1: Data Description

Data Field	Data Type	Definition
National Item Identification Number (NIIN)	Character(9)	Unique, nine-digit code that identifies each repairable item managed by the NAVICP sites.
Family Group Code (FGC)	Character(4)	Code used to identify similar items belonging to the same family. FGC is blank for non-family items.
Family Relationship Code (FRC)	Character(1), either "H" or "M"	Code used to identify the head of a family. The value "H" is used for family head, and "M" is used for members. FRC is blank for items with no family designation.
Document Number	Character(14)	Code that uniquely identifies each repair transaction.
Serial Number	Character(5)	Code used to uniquely identify different units with the same NIIN.
Quantity (QTY)	Numeric(5)	Quantity repaired per transaction.
Turn Around Time (TAT)	numeric(5)	Total reported repair time, in days, for each repair transaction. TAT starts when an item is received by the designated overhaul point (DOP) and ends when the DOP transfers the repaired item to a stock point.
Completion Date	date in YYDDD format	Completion date of repair.
Designated Overhaul Point (DOP)	Character(6)	Code that identifies the site that performed the repair. Six digit codes represent Department of Defense DOPs, known as **organic** DOPs, while three digit codes represent **commercial** (contractor) DOPs.
G Time	numeric(5)	Number of days that the DOP was awaiting parts necessary to complete the repair. If there was no waiting time, G Time is set equal to zero.

Data Field	Data Type	Definition
Commercial Indicator	Character(1), either "C" or blank	Code that identifies repair transactions that originated from a commercial repair database. Commercial Indicator is set to "C" when this is the case; otherwise it is left blank.
Exclude Indicator	character(1), either "Z", "P", or blank	Code that identifies data recognized by the forecasting tool as either recording errors (Z) or outliers (P), and thereby excluded from the UICP process. Excluded data are distinguished from "excluded repairable items" for which automated forecasts are not calculated.
Revised Days	numeric(3)	Set equal to TAT when the record was entered manually; otherwise it is set to zero.

APPENDIX C: REPAIRABLE ITEMS SELECTED FOR ANALYSIS

Fifteen repairable items are selected for analysis in this thesis. Table C.1 lists the item names, national identification numbers (NIIN), unit repair prices, and unit standard prices. Unit repair price is the price NAVICP paid to have an item repaired, while unit standard price is the price paid by a customer for a new or newly-overhauled item. The relative value or importance of the fifteen items with respect to all items managed by NAVICP-Phil is quantified in Tables C.2 to C.5. Table C.2 quantifies relative value or importance over the entire three-year database, while Tables C.3 to C.5 quantify relative value or importance in each of the three separate years that comprise the database. All prices are expressed in dollars for the year in which repair completions occur. Prices are not adjusted for inflation.

Table C.1: Fifteen Repairable Items Selected for Analysis

Item name	NIIN	Unit Repair Price (1998 US dollars)	Unit Standard Price (1998 US dollars)
Navigational Unit 1	01-054-3776	$10,658	$312,390
Inertial Navigation Unit	01-387-0348	10,658	312,390
Stabilizer, optics	01-300-0940	15,220	545,100
Gimbal assembly	01-011-0855	22,498	143,590
Servocylinder	01-351-3373	4,415	123,020
Servocylinder F/A-18	01-343-7026	8,226	92,840
Helo rotor blade CH-53E	01-316-3474	16,788	195,250
Module, film traction F/A-18	01-154-2794	11,894	91,000
Gyroscope, displacement	00-928-0072	5,517	41,330
Propeller	00-887-1944	60,277	155,720
Power Supply LAU-7/A-5	01-141-2735	932	4,310
Indicator, altitude	00-165-5838	1,853	9,060
Nozzle, turbine engine	00-411-6264	332	1,100
Starter, engine CH-46E	01-062-5846	1,007	10,690
Actuator assembly F404	01-139-7177	830	2,400

Table C.2: Characteristics of Items Selected For Analysis, 1996-1998

NIIN	Quantity Repaired	Total Days In Repair	Total Cost of Repairs (millions of US dollars)	Total Cost of Repaired Items (millions of US dollars)
01-054-3776	1,627	37,704	16.2	400.6
01-387-0348	1,040	26,283	10.4	259.4
01-300-0940	369	23,078	6.8	166.1
01-011-0855	1,283	151,916	28.9	157.9
01-351-3373	940	103,014	9.5	101.6
01-343-7026	1,196	121,038	9.4	99.0
01-316-3474	521	53,332	13.6	84.8
01-154-2794	712	47,793	9.6	71.4
00-928-0072	1,786	111,607	8.2	64.9
00-887-1944	502	75,337	20.9	63.2
01-141-2735	2,942	102,293	3.1	10.2
00-165-5838	2,381	111,763	4.1	18.4
00-411-6264	1,427	145,808	0.6	1.4
01-062-5846	1,405	202,912	1.7	13.1
01-139-7177	1,231	96,502	0.9	2.5
Total (top 10)	19,362	1,410,380	143.9	1,514.6
Total (all items)	459,537	39,954,766	2,120.0	13,574.8
Percentage	**4.2**	**3.5**	**6.8**	**11.2**

Total Days in Repair is the sum of repair turn-around time (RTAT) across all units repaired for the item. Total Cost of Repairs = Quantity times Unit Repair Price. Total Cost of Repaired Items = Quantity times Unit Standard Price.

Table C.3: Characteristics of Items Selected For Analysis - 1996

NIIN	Quantity Repaired	Total Days In Repair	Total Cost of Repairs (millions of US dollars)	Total Cost of Repaired Items (millions of US dollars)
01-054-3776	490	13,115	4.5	104.4
01-387-0348	301	13,197	2.8	64.1
01-300-0940	136	7,741	2.6	49.8
01-011-0855	559	40,110	12.6	63.8
01-351-3373	392	47,517	4.9	39.5
01-343-7026	261	16,753	1.4	19.3
01-316-3474	161	16,232	3.0	24.0
01-154-2794	283	15,659	2.7	28.8
00-928-0072	627	30,884	2.6	20.6
00-887-1944	137	13,745	6.2	13.9
01-141-2735	850	34,591	1.1	2.9
00-165-5838	979	41,068	1.9	7.0
00-411-6264	252	26,808	0.1	0.2
01-062-5846	526	43,932	0.8	4.5
01-139-7177	376	28,526	0.3	0.8
Total (15)	6,330	389,878	47.5	443.6
Total (all items)	128,564	11,051,817	597.0	3,422.9
Percentage	**4.9**	**3.5**	**8.0**	**13.0**

See caption on Table C.2 for definitions of the tabulated quantities.

Table C.4: Characteristics of Items Selected For Analysis - 1997

NIIN	Quantity Repaired	Total Days In Repair	Total Cost of Repairs (millions of US dollars)	Total Cost of Repaired Items (millions of US dollars)
01-054-3776	636	13,028	6.4	139.7
01-387-0348	383	5,369	3.8	84.1
01-300-0940	109	5,776	2.3	48.7
01-011-0855	383	63,551	8.6	45.1
01-351-3373	278	28,004	3.4	28.9
01-343-7026	420	35,586	3.8	32.0
01-316-3474	227	19,634	8.3	34.9
01-154-2794	260	22,969	4.9	27.3
00-928-0072	486	26,726	1.9	16.5
00-887-1944	270	44,954	9.0	34.5
01-141-2735	1,053	35,523	1.0	2.8
00-165-5838	803	34,235	1.1	6.0
00-411-6264	576	57,264	0.2	0.5
01-062-5846	389	42,309	0.4	3.4
01-139-7177	514	44,390	0.3	1.0
Total (top 15)	6,787	479,318	55.5	505.1
Total (all items)	165,153	14,273,179	735.2	4,580.1
Percentage	**4.1**	**3.4**	**7.6**	**11.0**

See caption on Table C.2 for definitions of the tabulated quantities.

Table C.5: Characteristics of Items Selected For Analysis - 1998

NIIN	Quantity Repaired	Total Days In Repair	Total Cost of Repairs (millions of US dollars)	Total Cost of Repaired Items (millions of US dollars)
01-054-3776	501	11,561	5.3	156.5
01-387-0348	356	7,717	3.8	111.2
01-300-0940	124	9,561	1.9	67.6
01-011-0855	341	48,255	7.7	49.0
01-351-3373	270	27,493	1.2	33.2
01-343-7026	515	68,699	4.2	47.8
01-316-3474	133	17,466	2.2	26.0
01-154-2794	169	9,165	2.0	15.3
00-928-0072	673	53,997	3.7	27.8
00-887-1944	95	16,638	5.7	14.8
01-141-2735	1,039	32,179	1.0	4.5
00-165-5838	599	36,460	1.1	5.4
00-411-6264	599	61,736	0.2	0.7
01-062-5846	490	116,671	0.5	5.2
01-139-7177	341	23,586	0.3	0.8
Total (top 15)	6,245	541,184	40.9	565.9
Total (all items)	165,820	14,629,770	787.7	5,571.8
Percentage	**3.8**	**3.7**	**5.2**	**10.2**

See caption on Table C.2 for definitions of the tabulated quantities.

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APPENDIX D: TRANSFORMING RTAT USING NATURAL LOGARITHMS

Figure D.1 provides normal QQ-plots of RTAT residuals for all 15 repairable items identified for analysis. Residuals for items repaired by a single DOP are obtained from a one factor analysis of variance (ANOVA) that explained RTAT using only the repair completion quarter. Residuals for items with multiple DOPs are obtained from an additive two-factor ANOVA based on repair completion quarter and DOP. Departures from linearity in these plots indicate a lack of normality of residuals. Fourteen of the 15 QQ-plots suggest pronounced nonnormality. The "U" shapes of many of these plots are characteristic of positively skewed distributions. Only for the Nozzle, turbine engine, (NIIN 00-411-6264) does the distribution of RTAT approach normality.

Figure D.2 shows the QQ-plots of residuals obtained after RTAT is transformed by the natural logarithm for the 15 items identified for analysis. In several cases the distributions remain skewed even after the logarithm transformation is applied. Evidence of heavy tails is also indicated by the "S" shapes of a number of the plots. Nonetheless, the logarithm transformation generally results in more symmetric distributions.

Figures D.3 and D.4 provide further evidence in favor of the logarithm transformation. These figures show boxplots for the untransformed and transformed RTAT values, respectively, broken down by quarter and DOP. Figure D.3 boxplots indicate that the RTAT distributions are positively skewed with nonconstant variance across the 12 quarters and two DOPs. In Figure D.4 the boxplots appear to be more symmetric with variances that are more stable across groups.

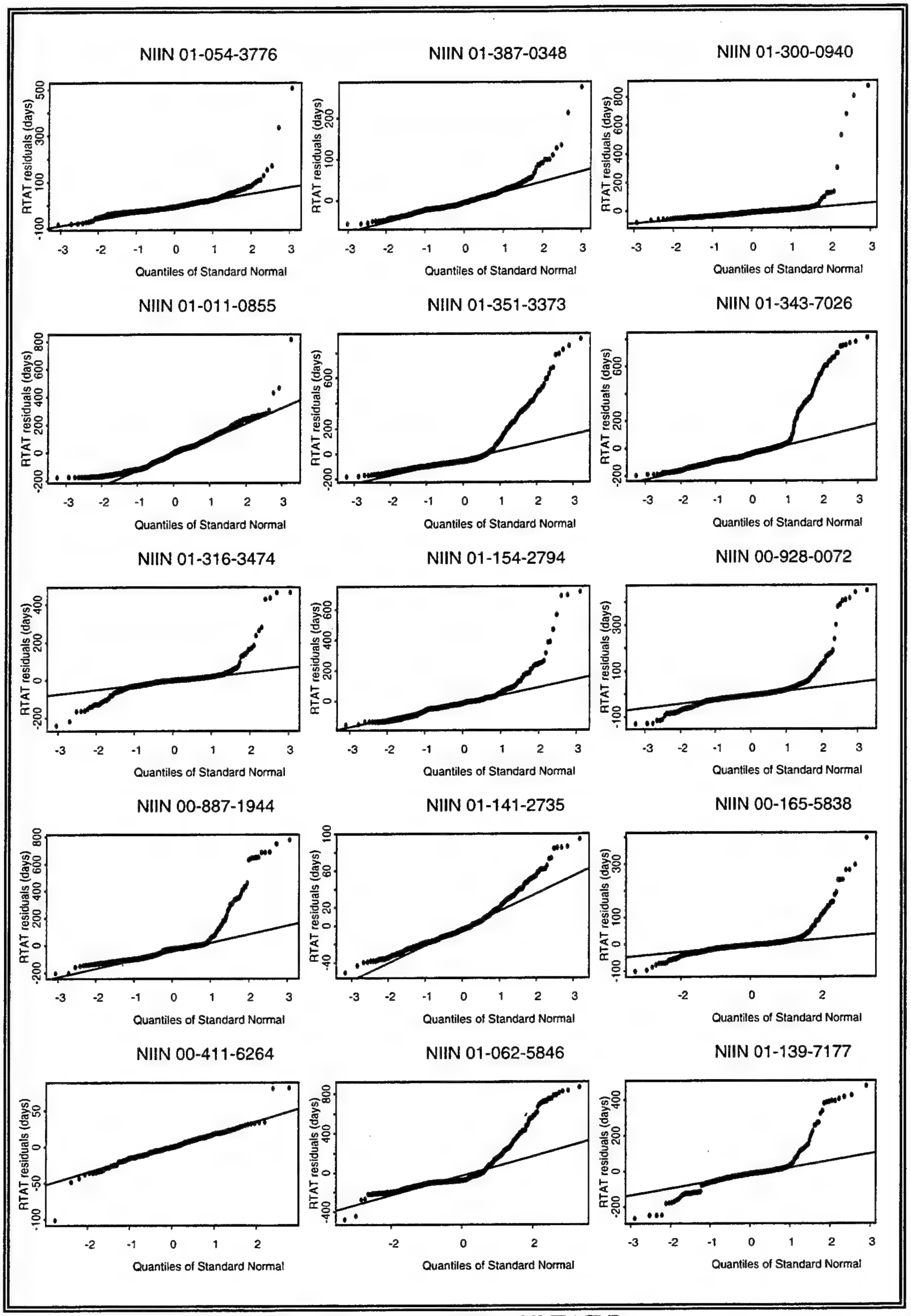

Figure D.1: QQ-Plots Indicate Non-Normality of RTAT Data

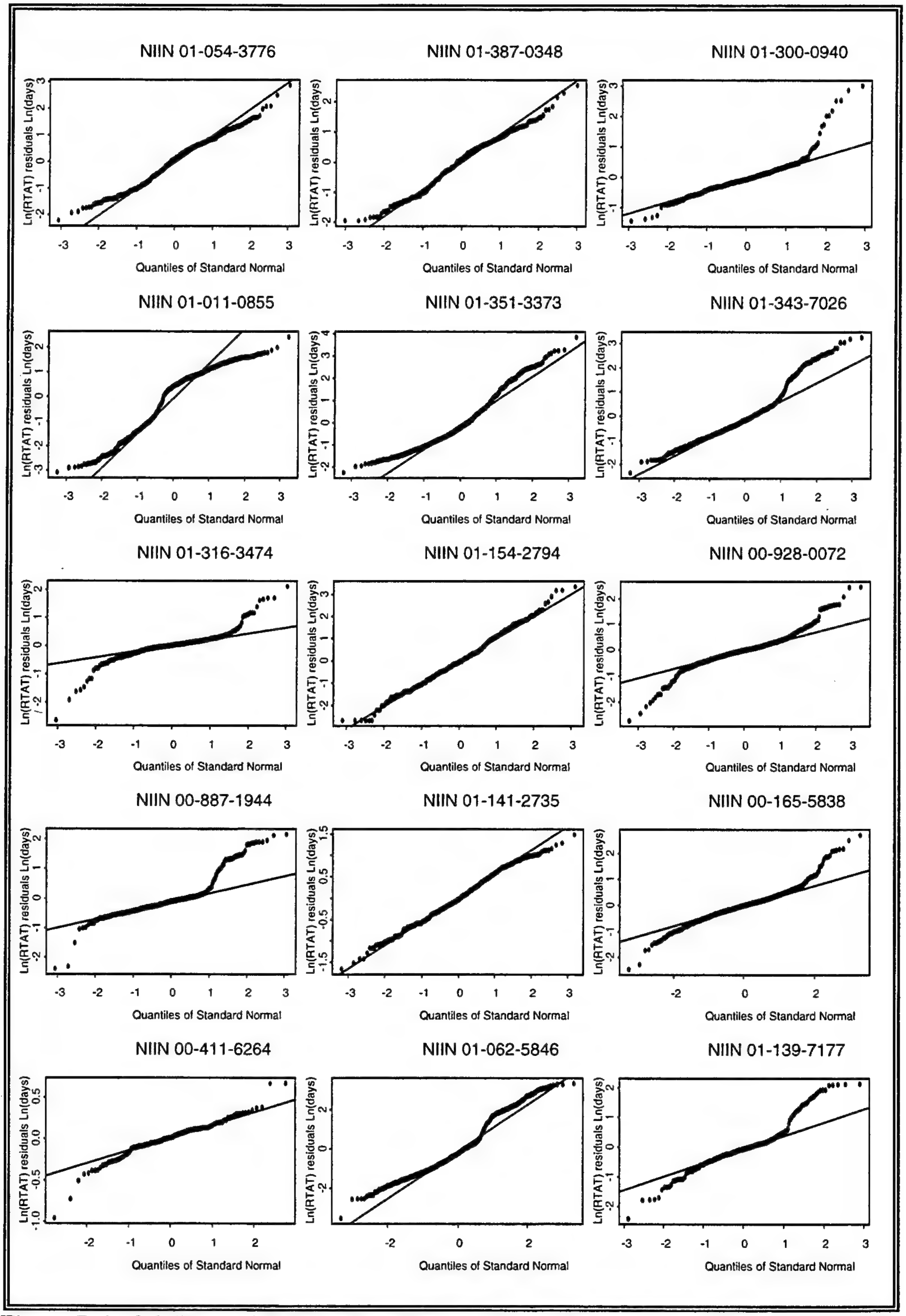

Figure D.2: QQ-Plots of RTAT Transformed Using Natural Logarithm

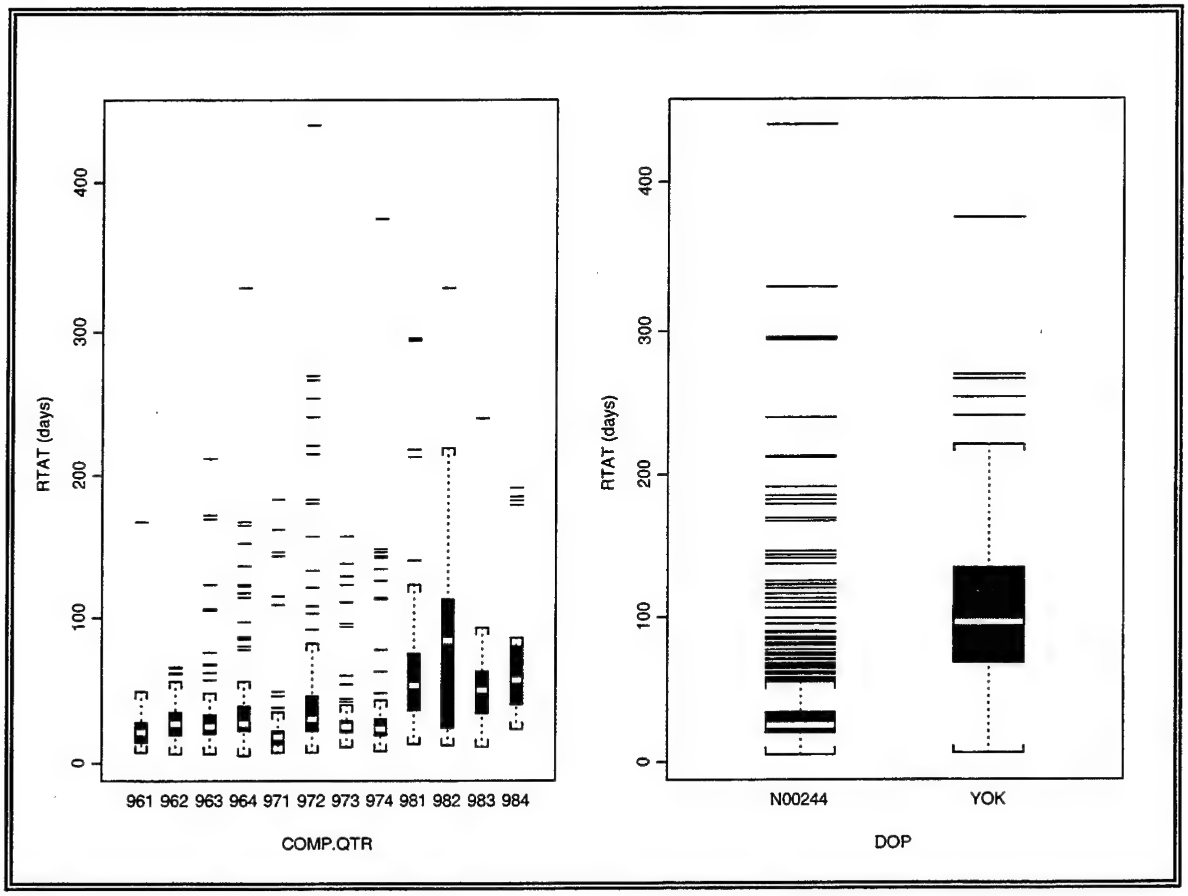

Figure D.3: Boxplots for Repair Turn-Around Times for NIIN 00-165-5838 Broken Down by Quarter and DOP. On the horizontal axis of the plot on the left (repair completion quarter) quarters are represented in YYQ format. On the horizontal axis of the plot on the right (designated overhaul point) N00244 and YOK are codes representing two different DOPs.

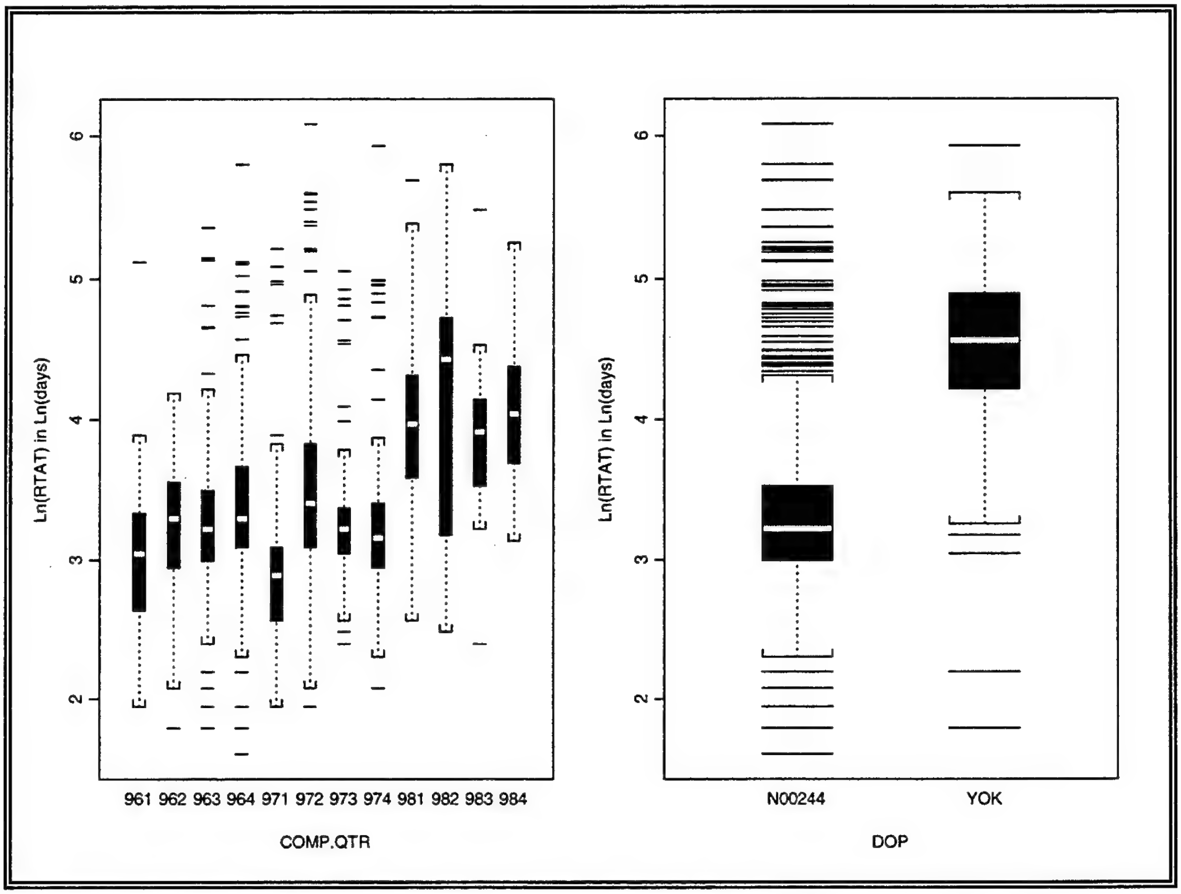

Figure D.4: Boxplots for Repair Turn-Around Times, Logarithm Transformed, for NIIN 00-165-5838 Broken Down by Quarter and DOP See caption on Table D.3 for definitions of horizontal axis labeling.

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APPENDIX E: REGRESSION MODELS AND MODEL DIAGNOSTICS FOR THE POWER SUPPLY LAU-7/A-5, NIIN 01-141-2735

Two linear regression models are formulated for each of the repairable items considered in this thesis that are repaired by one designated overhaul point. Ordinary Least Squares are used to obtain estimates of the model parameters. The models and model diagnostics for one item, the Power Supply, LAU-7/A-5 (NIIN 01-141-2735), are presented below. Model 1 is a regression of the natural logarithm of RTAT (dependent variable) on the previous-quarter quantity-weighted average of the natural logarithm of RTAT or Lagged Mean (predictor variable). Model 2 includes the same predictor variable as the first model plus three additional predictor variables: *Pending*, *PRatio*, and *MedPend*. The formulas for the corresponding models are shown in Chapter IV. Statistics, coefficient and intercept values for Model 1 are provided in Table E.1.

Table E.1: Ordinary Least Squares Regression Results for Model 1

N	R^2	F	P-value (F)	σ	β_0	β_1
378 (df=376)	0.02	7.373	0.01	0.54	5.19 (8.14)	0.54 (2.71)

N = number of repair observations, R^2 = coefficient of determination, F = test statistic value of model utility test, σ = estimated residual standard deviation. Numbers in parentheses below regression coefficients are t-ratios.

The t statistics for both the intercept and coefficient in the first model are significant at the $\alpha = 0.05$ level which indicate that intercept and coefficient values are not zero. The F statistic formed in the model utility test is also highly significant and indicates that the model is useful. However, the model explains little of the total variance of natural logarithm of RTAT since $R^2 .= 0.02$.

Statistics, coefficient and intercept values for Model 2 are provided in Table E.2.

Table E.2: Ordinary Least Squares Regression Results for Model 2

N	R^2	*F*	P-value	σ	β_0	β_1	β_2	β_3	β_4
378 (df=373)	0.19	21.37	0.00	0.493	5.67 (7.02)	-0.74 (-3.10)	.008 (3.95)	-3.07 (-2.36)	0.08 (1.22)

See Table E.1 for a description of column entries

The estimated regression intercept (β_0) and three of the four coefficients (β_1, β_2, β_3) are significant at the $\alpha = 0.05$ level. Model 2 explains 19% of total variance of natural logarithm of RTAT.

Two diagnostic plots are formed for each model. First, residuals are plotted against fitted values. Figures E.1 and E.2 show that residuals do not appear to exhibit any distinct patterns in either model, and in each model they are seemingly distributed about zero according to a normal distribution. The QQ-plots shown in Figures E.3 and E.4 indicate that the residuals are nearly normally distributed under either model.

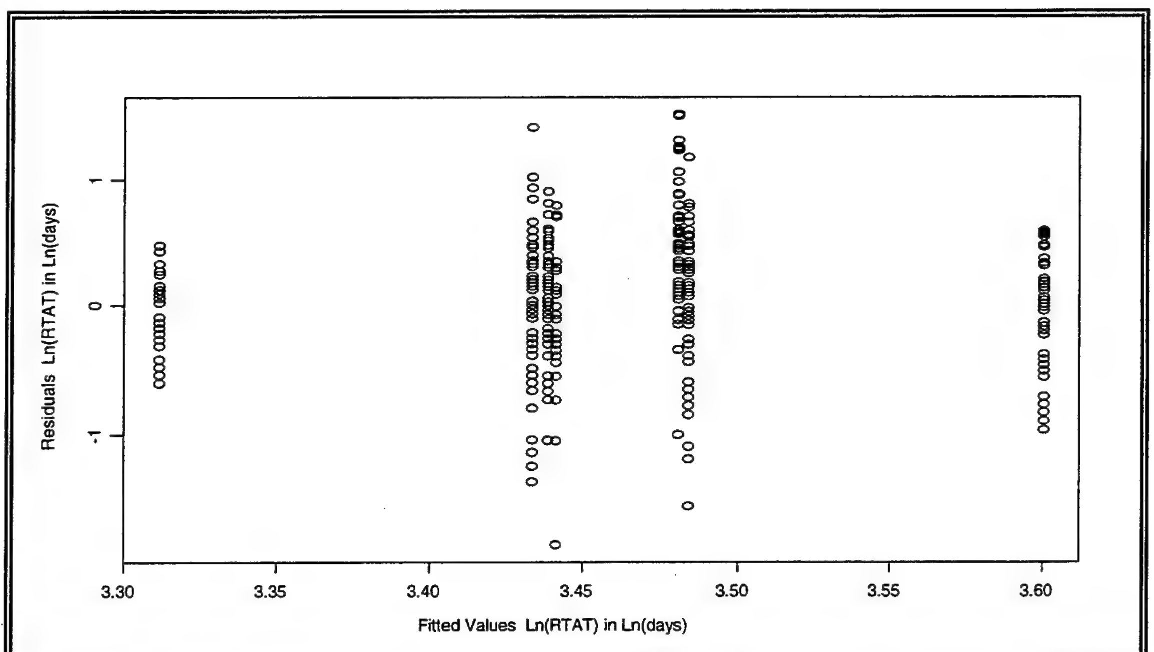

Figure E.1: Residuals Versus Fitted Values – Model 1, Power Supply, LAU-7/A-5

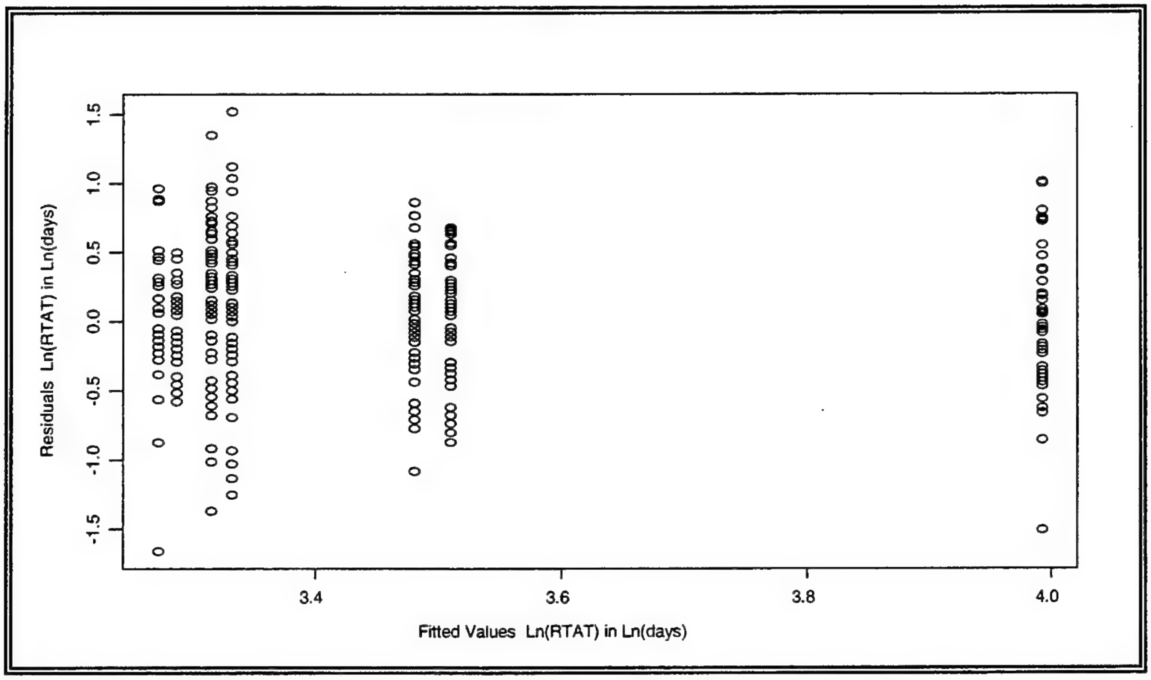

Figure E.2: Residuals Versus Fitted Values – Model 2, Power Supply, LAU-7/A-5

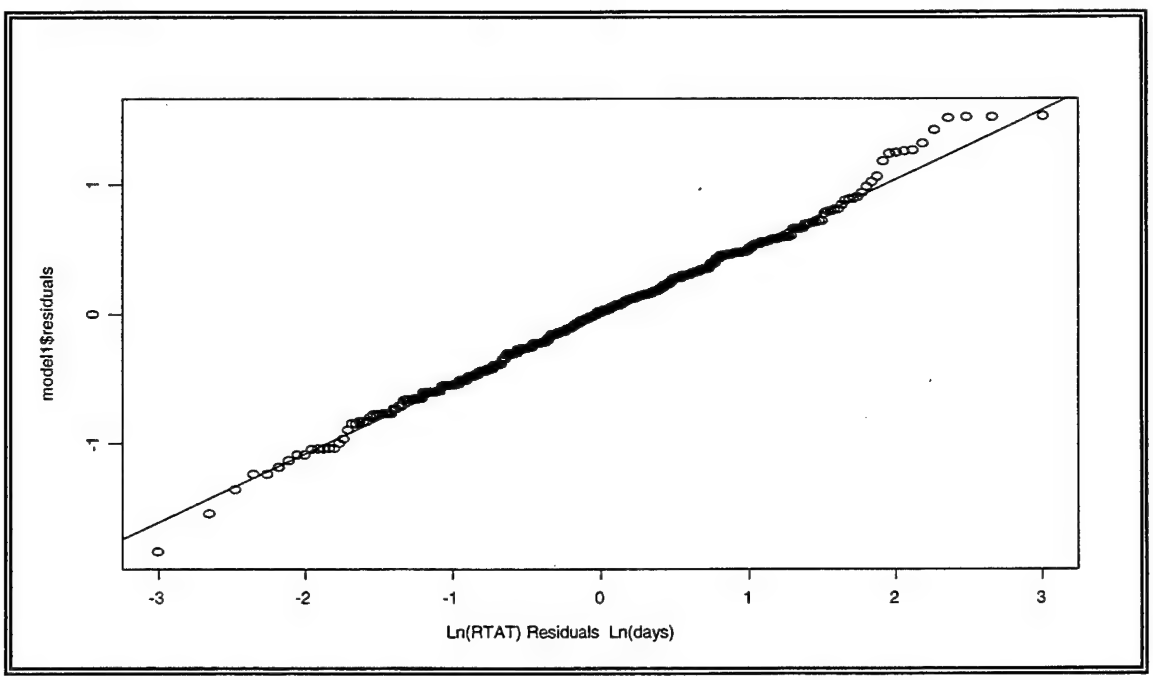

Figure E.3: QQ-Plot of Residuals - Model 1, Power Supply, LAU-7/A-5

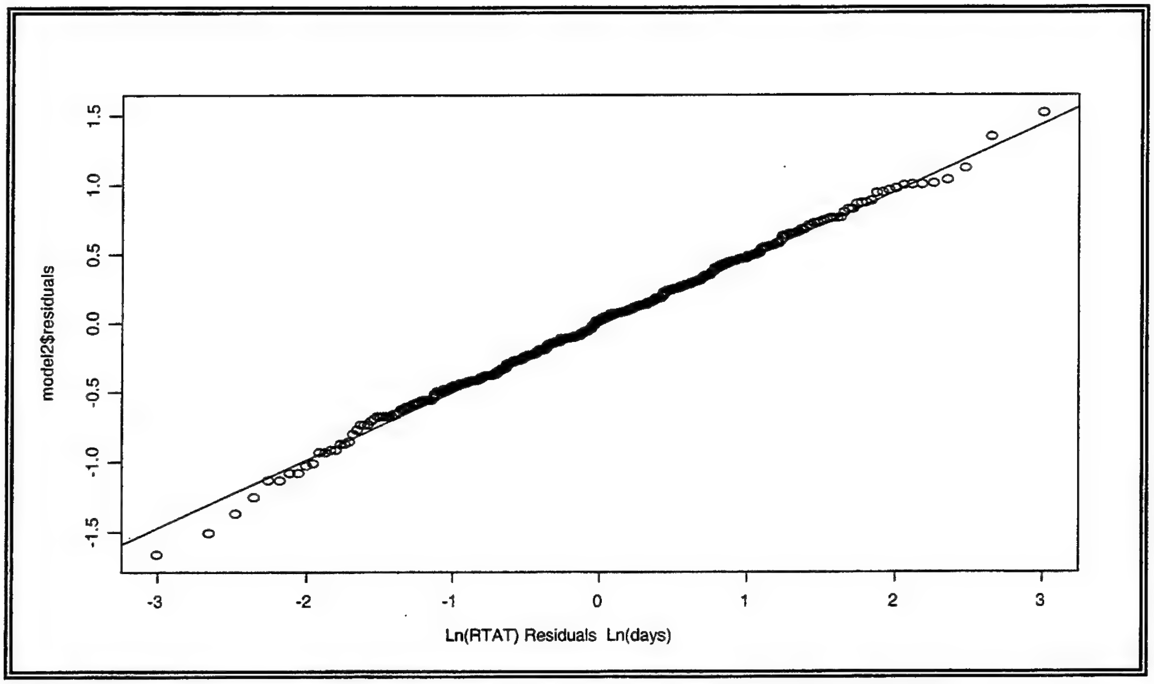

Figure E.4: QQ-Plot of Residuals - Model 2, Power Supply, LAU-7/A-5

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